Are there private information benefits to participating in a public earnings conference call?

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Abstract

We examine whether analysts who participate in earnings conference calls by asking questions receive private information benefits relative to analysts who do not ask questions. Private information benefits accrue to a participating analyst when a manager’s response to the analyst’s question uniquely complements that analyst’s private information set. Our evidence is consistent with participating analysts receiving beneficial private information. Specifically, we find that the initial annual earnings forecasts subsequent to a conference call are more accurate and more timely for participating analysts. We also find that participating analysts are more likely to reciprocate by upgrading (not downgrading) a firm’s stock recommendation upon receiving good (bad) earnings news. Our results suggest that managers and analysts continue to exchange private benefits in the Post Regulation FD era.

Key words: Conference calls, private information benefits, financial analysts, Regulation FD, forecast accuracy, forecast timeliness

JEL classifications: M41, G24, G29, G38, K22
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1.0 Introduction

Prior to Regulation Fair Disclosure (Reg FD), earnings conference calls, where managers discuss the firms’ results and prospects, were accessible only to the privileged few. Such preferential access offered significant private information and trading advantages to the investors and analysts who were allowed access by management. To level the information playing field across market participants and to forbid preferential access to management, the Securities and Exchange Commission implemented Reg FD in October 2000. With a prohibition on the private communication of material information, conference calls became “open” by being accessible to anyone with either a phone line or an internet connection (Bushee et al. 2004). However, while all investors and analysts are allowed to listen in on the call, only a subset of analysts is allowed by management to ask questions (Mayew 2008). The purpose of this study is to investigate whether analysts who participate in earnings conference calls by asking questions receive private information benefits relative to nonparticipating analysts who do not ask questions.

Our study is motivated by the continuing debate over whether Reg FD has achieved its intended objective to reduce selective disclosure. Some researchers (e.g., Bushee et al. 2004; Gintschel and Markov 2004; Mohanram and Sunder 2006) have provided evidence consistent with Reg FD leveling the playing field by curtailing selective disclosure. Despite this evidence, practitioners (e.g., Mayo 2002; Lowengard 2006; Mayo 2006; Erdos and Morgan 2008) and the Securities and Exchange Commission (Cox 2005) continue to voice concerns that unequal conference call access puts nonparticipating analysts at an informational disadvantage. Analysts contend that because their questions are being ignored during the question and answer portion of the conference call, they cannot generate the insights necessary to successfully compete in the
market for information. These concerns are grounded in the theoretical notion that public information can play a complementary role to an individual’s information set (Barron et al. 2002; Kim and Verrecchia 1997).

In contrast, Libby et al. (2008) question the exact nature of the benefits to analysts from conference call participation given that the answers to conference call questions are immediately made public. That public answers would eliminate any private information benefit to an individual analyst is based on the notion that public information substitutes for private information (Verrecchia 1982; Diamond 1985). Our study seeks to provide empirical evidence on the existence and extent of private information benefits that may accrue to analysts who receive preferential treatment from management by being allowed to ask questions in public earnings conference calls.

Using post-Reg FD earnings conference call transcripts, representing 1,919 firms and 3,246 analysts between 2002 and 2005, we first identify which analysts from the I/B/E/S population participated in the firms’ quarterly earnings conference calls. We classify analysts as participating (nonparticipating) if they ask (do not ask) a question on the conference call and investigate whether participating analysts accrue more private information benefits than nonparticipating analysts.

Since private information is not observable, directly measuring the nature of private information at the individual analyst level is not possible. We therefore seek evidence

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1 One prestigious analyst, in testimony to the U.S. Senate Committee on Banking, Housing and Urban Affairs, stated that even subsequent to Reg FD, managers still have tools to informationally “handicap” certain analysts using the analogy that some analysts are “still doing the equivalent of playing basketball with one hand behind our back” (Mayo 2002). In the appendix we provide an analytic example based on Barron et al. (2002) and Kim and Verrecchia (1997) that illustrates the potential advantages of being able to ask a public conference call question.  
2 Barron et al. (1998) have developed the BKLS measure which proxies for the extent of private information collectively held among all analysts following a firm but does not accommodate (1) private information measurement at the individual analyst level or (2) whether such information is beneficial. As such, we are unable to use this measure in our empirical tests.
consistent with analyst possession of beneficial private information. Private information is beneficial to an analyst if it is rewarded by the analyst’s clients. Analyst investor clients, who seek to uncover profitable trading opportunities, not surprisingly value analysts who provide “useful and timely” information (Johnson 2005). Since analysts contend that conference call access helps them better informationally serve their clients, we operationalize “useful and timely” information via the accuracy and timeliness of the initial annual earnings forecast issued subsequent to the conference call.

Levels, changes, and propensity score matched sample empirical specifications provide corroborating evidence that the relative accuracy of participating analysts’ initial annual earnings forecasts is greater than that of nonparticipating analysts. Participating analysts also offer the market more timely initial forecasts of upcoming annual earnings following the conference call compared to nonparticipating analysts. These results suggest that access to management through questioning during earnings conference calls helps analysts provide superior information to their investing clients.

We acknowledge that, despite using a number of empirical research designs, we cannot fully rule out analyst effort as a correlated omitted variable. In other words, unobservable analyst effort may still explain both conference call participation and the accuracy and timeliness of analyst forecasts. To mitigate this concern and provide additional insights into the effects of conference call participation, we consider the economic exchange purported to occur when managers allow conference call participation. If managers allow analyst participation in exchange for the analyst maintaining a favorable stock recommendation on the firm, we should observe recommendation activity in response to analyst specific news that reflects incentives to maintain rapport with firm management. This prediction is consistent with the discrimination
hypothesis (Francis et al. 2004) that posits managers exchange private information for favorable stock recommendations from analysts (Cox 2005; Chen and Matsumoto 2006; Lowengard 2006; Mayew 2008).

This would imply that upon receipt of bad (good) news about the firm, participating analysts should be less (more) likely to downgrade (upgrade) than nonparticipating analysts. Differential effort is unlikely to result in this asymmetric prediction because it is unclear why simply putting forth more effort would result in differential responses to receiving good and bad news. Consistent with private information benefits rather than differential effort, we find that when updating recommendations for firms that have fallen below (exceeded) each analyst’s individual quarterly earnings forecast, participating analysts on average are 11% (10%) less (more) likely to downgrade (upgrade) the stock than nonparticipating analysts over the subsequent 90 days.

While our evidence collectively is consistent with information benefits accruing from conference call participation, superior information may not be the only benefit for the analyst. As Libby et al. (2008) suggests, analysts may enhance their reputations with institutional investors by being publicly visible. Empirically it is difficult to directly measure reputation enhancement or other benefits outside of the information advantage. However, to provide preliminary insights on this issue, we examine whether conference call participation is associated with analyst career outcomes. We find that participating analysts have lower turnover in the subsequent year relative to nonparticipating analysts, consistent with analysts reaping relative rewards by obtaining conference call access. We view the identification and quantification of benefits other than information benefit as an important area for future research.
This paper makes several contributions. First, we offer evidence that conference call access, despite being public, does seem to provide private information benefits to participating analysts. By documenting the existence and extent of these benefits, we provide relevant insights to regulators as they continue to evaluate the success of Reg FD in leveling the information playing field. Relatedly, our results provide evidence for regulators and investors alike regarding one potential driver for the optimism observed in analyst stock recommendations. Since private information benefits are not provided for free by economically rational managers, conference call participation, like investment banking ties in the pre-Reg FD period (O’Brien et al. 2005), becomes an observable proxy for analysts who have incentives to please management.

Second, we add to the literature that suggests public information can have private information benefits. Barron et al. (2002) show that as a group, analysts possess more private information after the public release of earnings. Our research identifies a particular set of these analysts, namely participating analysts, who potentially drive the generation of important private information after the public earnings event. Further, our results corroborate the pre-Reg FD findings of Chen and Matsumoto (2006) that analysts with access to management deliver more accurate earnings forecasts in the post-Reg FD period.

Third, we offer new insights on the accuracy and timeliness tradeoff analysts face when forecasting earnings (Schipper 1991; Guttman 2009). While information is more useful when it is both timely and accurate, the literature on earnings forecasting has repeatedly documented an inverse relationship between accuracy and timeliness, based on the notion that more accurate forecasts are issued as the earnings report date approaches. Brown and Mohd (2003) highlight timeliness as one of the single most important determinants of earnings forecast accuracy. Our finding that participating analysts are both more timely and more accurate in their forecasts...
provides support for the information benefits to participation and is consistent with the theoretical prediction in Guttman (2009) that analysts with more precise (i.e. accurate) private information will forecast earlier.

Fourth, we begin to answer the question posed in Libby et al. (2008) regarding the specification of the exact nature of the benefits of conference call access. Our investigation should be viewed as a preliminary step in this direction. Our results point toward private information benefits as one identifiable benefit. However, there may be other benefits as we find that, incremental to information benefits, participating analysts have more favorable career outcomes in the subsequent year.

Finally, this paper complements recent evidence suggesting managers and analysts continue to reciprocally exchange private benefits in the Post Regulation FD era. The extant literature suggests that analysts provide favorable stock recommendations to firms whose managers offer personal favors to analysts (Westphal and Clement 2008) and to managers who grant the analyst with lucrative board of director positions (Cohen et al. 2008). We build on Mayew’s (2008) contention that analysts issue favorable recommendations to acquire conference call access by documenting that managers reciprocate via private information benefits from call participation.

The paper proceeds as follows. Section 2 reviews the literature and develops the hypotheses. Section 3 outlines the sample selection, variable measurement and research design. Section 4 provides empirical results, Section 5 assesses the robustness of the findings, and Section 6 concludes.
2.0 Related Literature and Hypothesis Development

The SEC issued Reg FD in October 2000 to level the information playing field among analysts and investors by prohibiting management from selectively disclosing material information to some analysts and not others. Under Reg FD, managers must publicly disseminate material information, thereby eliminating any information advantage that an individual analyst may have otherwise obtained via private communications with management.

The notion that public information would substitute for private information is consistent with theoretical models of disclosure (Verrecchia 1982; Diamond 1985). Empirically, Bowen et al. (2002) show that firms choosing to host conference calls prior to the passage of Reg FD helped level the playing field among analysts, consistent with public information eliminating the private information advantage of some analysts. Gintschel and Markov (2004) document that the informativeness of analyst outputs, in particular, the price impact of analyst forecasts, declined subsequent to Reg FD consistent with effectiveness of Reg FD in reducing selective disclosure. Mohanram and Sunder (2006) provide additional evidence that public conference call access leveled the playing field to some degree in the one year window surrounding the passage of Reg FD, particularly for non-all-star analysts.

However, a growing number of analysts have suggested that a level playing field still does not exist, citing differential conference call access as the culprit (Mayo 2002; Kelly 2003; Davis 2004; Morgenson 2005; SIA 2005; Lowengard 2006; Mayo 2006; Erdos and Morgan, 2008).3 The SEC has taken notice and has identified differential conference call access as a particular concern (Cox 2005). The economic underpinning of these concerns is the notion that

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3 Janakiraman et al. (2006) examine whether the timeliness of analysts’ first earnings forecasts differs across favored and nonfavored analysts. Their proxy for favored analysts are leaders in providing forecasts, i.e., quickest to provide forecasts. They report mixed evidence on whether Reg FD eliminated the timing advantage that favored analysts enjoyed pre-Reg FD.
being able to participate in a conference call uniquely serves the participating analyst by complementing her existing private information. Assuming analysts ask questions conditional on their existing private information, the public answer to such questions will uniquely complement the information set of the asking analyst relative to analysts who do not ask questions (see Appendix 1 for a formal derivation). Both theoretical and empirical research suggests that public information disclosures, such as earnings announcements, can indeed facilitate the generation of uniquely private information (Barron et al. 2002; Kim and Verrecchia 1997).

Whether, and to what extent, analysts reap benefits from any potential private information derived from public answers to their questions in the post-FD conference call setting remains an unresolved issue in the literature. Consistent with private information benefits accruing to participating analysts, analyst subjects in Libby et al. (2008) claim that conference call access, even though public, is important to analysts in analyzing the firm. Mayew (2008) provides evidence consistent with managers granting more conference call access to more favorable analysts, potentially consistent with analyst “payment” for private information benefits.

Both of these studies, however, offer caveats regarding whether one can conclude that analysts actually receive private information benefits. Libby et al. (2008) note that the exact nature of the benefits arising from conference call participation is unclear given that the answers to conference call questions are immediately made public. Mayew (2008) concedes that managers may grant conference call access to favorable analysts because managers prefer to discuss the firm’s prospects with analysts who share their same optimistic view of the firm’s future. Such activity would not necessarily put nonparticipating analysts at an informational disadvantage.
In this paper we attempt to fill the void in the literature on the existence and extent of private information benefits from participating in the conference call. Private information is beneficial to an analyst if it is rewarded by the analyst’s investor clients. Analyst investor clients, seeking to uncover profitable trading opportunities, state they value analysts who provide them both “useful” and “timely” insights about the future prospects of the companies they cover (Johnson 2005, Bagnoli et al. 2008). To investigate whether conference call participation helps facilitate the generation of private information of this sort, we operationalize these information attributes of usefulness and timeliness via the accuracy and timeliness, respectively, of the initial annual earnings forecast issued subsequent to the conference call.

We acknowledge that institutional investors do not value aggregate analyst outputs like stock recommendations and earnings forecasts per se as highly as individual insights about a firm’s value drivers (Johnson 2005; Bagnoli et al. 2008). As such, our proxies for beneficial private information based on properties of the initial annual earnings forecasts provided immediately subsequent to the conference call are constructed under the assumption that these earnings forecasts properties are correlated with the informational insights that institutional investors find valuable.

If asking a conference call question yields private information benefits, the initial forecasts of future earnings issued by participating analysts after the conference call should be both more accurate and more timely relative to nonparticipating analysts. Stated formally:

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4 Guttman (2009) uses this assumption to model the timeliness of analyst forecasts, noting that investors benefit from analyst insights by receiving early access to information that can be used to make trading decisions.

5 Bagnoli et al. (2008) provide a list of analyst attributes institutional investors value. During the post-FD period analyzed, providing “useful and timely calls” ranked 4th while earnings estimates and stock selection ranked between 9th and 12th. Consistent with this notion, Groysberg et al. (2008) note that the properties of earnings forecasts such as accuracy and timeliness are not explicitly part of analysts’ compensation contracts. In private discussion, the managing director and director of research at a prominent sell-side research firm also noted that institutional investor clients have their own personnel to map information into projections of earnings and stock recommendations and therefore valued individual insights from sell-side analysts more than their aggregated overall opinions about future earnings and firm value.
H1a: Ceritus paribus, participating analysts’ initial annual earnings forecasts following the conference call are more accurate than nonparticipating analysts’ forecasts.

H1b: Ceritus paribus, participating analysts’ initial annual earnings forecasts following the conference call are more timely than nonparticipating analysts’ forecasts.

3.0 Sample Selection, Research Design and Variable Measurement

3.1 Sample

Our empirical analysis uses earnings conference call transcripts from the Thomson StreetEvents database. We first extract the 27,497 quarterly earnings conference call transcripts available on StreetEvents between July 2001 and March 2005 for which we could obtain a firm identifier in I/B/E/S. Our sampling period begins in July 2001 because this is the inception of the StreetEvents database coverage of earnings conference calls. The sample ends in March 2005 because this was the last date we were able to obtain the I/B/E/S analyst and broker translation files. I/B/E/S translation files facilitate the mapping of analyst names and brokerages from the transcripts to the numeric codes for the respective analyst and brokerage in I/B/E/S. Since 2005, I/B/E/S stopped providing these translation files to researchers.

From our initial extraction of transcripts, we remove 835 firm quarter observations where I/B/E/S did not list at least one identifiable analyst with both an outstanding quarterly earnings forecast for the quarter in question and an outstanding recommendation as of the conference call date. The analyst following associated with this resulting set of 26,662 firm quarter observations represent our proxy for the potential population of analysts who could participate in the firm’s quarterly earnings conference call. From each conference call transcript, we proceed

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6 We do not impose any restrictions regarding staleness of either the quarterly earnings forecast or the stock recommendation at this point in the sample selection process.

7 The theoretical potential set of participants include I/B/E/S analysts who cover the firm, I/B/E/S analysts who do not cover the firm, analysts not on I/B/E/S, bankers, institutional investors and individual investors. Identifying this theoretical population and measuring the nature of the information sets contained by participants other than I/B/E/S analysts following the firm is cost prohibitive. Mayew (2008) documents that at the median, managers take
to extract the name and broker affiliation of each analyst who asked a question during the conference call. Using the I/B/E/S translation files, we then code a participating analyst as one who asked a question on the firm’s quarterly earnings conference call.

Separately, we obtain individual analyst annual earnings forecast data from the I/B/E/S detail file. We focus on annual forecasts because analysts commonly issue them multiple times during a fiscal year, which allow us to empirically measure revision activity around conference call events and conduct a changes analysis. We were able to obtain annual earnings forecasts for 149,210 analyst firm quarters where the firm announces earnings within 45 (90) days of the quarter (year) end, and the analyst issues a one-year-ahead annual earnings forecast within 90 days both before and after each quarterly earnings announcement between July 1, 2001 and March 30, 2005.

We restrict our forecast sample to firms that have at least three analysts following the firm in order to calculate meaningful relative measures in our empirical tests. This reduces the forecast sample to 138,216 analyst firm quarters. Combining the earnings forecast sample with the conference call sample yields 71,542 analyst firm quarter observations. Eliminating all firm-quarters during our period where the conference calls have no variation in the participating status of analysts (i.e., either all analysts asked questions or no analysts asked questions) reduces the sample to 57,449 analyst firm quarters. Finally, requiring a measure of analyst forecast frequency over the preceding calendar year reduces our final sample to 57,443 analyst firm quarters observations, which represent coverage of 8,516 firm quarter conference calls of 1,919 unique firms by 3,246 unique analysts from 265 unique brokerages. Although the conference call transcript data is available from July 2001, our final sample begins in the first quarter of questions from 9 non-corporate participants, firms are covered by 6 I/B/E/S analysts, and 3 I/B/E/S analysts ask questions.
2002 because (i) in the early periods conference call transcripts were sparsely populated and (ii) sample restrictions due to I/B/E/S data availability result in no observations for 2001. Our sample selection process yields a sample of analysts who are likely to have interest in covering the firm and maintain such interest after the conference call event, since we require recent analyst forecasting activity both before and after the call.8

3.2 Research Design

3.2.1 Accuracy of annual earnings forecasts

We investigate whether the participating analysts issue more accurate initial annual earnings forecasts than nonparticipating analysts as predicted in H1a using both a levels and changes analysis. Our levels analysis follows the extant literature (Clement and Tse 2003; Clement and Tse 2005; Ke and Yu 2006) and estimates the determinants of relative accuracy using a pooled cross-sectional OLS model with standard errors clustered by analyst:

\[
ACC_{R_{i,j,t}}^{post} = \beta_0 + \beta_1 \text{Participate}_{i,j,t} + \beta_2 F_{Exper}_{R_{i,j,t}} + \beta_3 T_{Exper}_{R_{i,j,t}} + \beta_4 \ln \text{Follow}_{i,j,t} + \beta_5 \text{Firms}_{R_{i,j,t}} + \beta_6 \text{Broker}_{R_{i,j,t}} \\
+ \beta_7 \text{Horizon}_{R_{i,j,t}}^{post} + \beta_8 \text{ForFreq}_{R_{i,j,t}} + \beta_9 ACC_{R_{i,j,t}}^{pre} + \varepsilon_{i,j,t}
\]

(1a)

The dependent variable, \( ACC_{R_{i,j,t}}^{post} \), is the forecast accuracy of analyst \( i \)'s first forecast revision of firm \( j \)'s annual earnings issued after quarter \( t \)'s earnings announcement relative to other analysts forecasting for firm \( j \). Formally, \( ACC_{R_{i,j,t}}^{post} = 100 - \frac{\text{absFErrank}_{i,j,t}^{post}}{\text{Follow}_{i,j,t}} \times 100 \),

where \( \text{absFErrank}_{i,j,t}^{post} \) is the rank of the absolute forecast error of an analyst’s initial forecast of upcoming annual earnings after the conference call among the forecasting analysts and \( \text{Follow} \) is the number of analysts issuing such a forecast. \( \text{absFErrank} \) takes on low values for small forecast errors and high values for large forecast errors, yielding a range for \( ACC_{R_{i,j,t}}^{post} \) between 0 and

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8 This works against finding results if lack of access is so detrimental that analysts drop coverage and hence are excluded from our sample.
100, where higher scores indicate more accurate forecasts. The use of relative forecast accuracy instead of raw forecast accuracy helps alleviate differences in forecasting environments that can exist across firms and accommodates different levels of analyst following across firms (Ke and Yu 2006; Hong and Kubik 2003). \( \text{Participate}_{i,j,t} \) is an indicator variable that equals 1 if analyst \( i \) asked a question on firm \( j \)’s quarter \( t \) conference call, and zero otherwise. \( H1a \) predicts \( \beta_1 > 0 \).

Drawing appropriate inferences on \( \beta_1 \) requires controls for analyst effort, since effort could explain both conference call participation and better forecast accuracy. Unfortunately, effort is unobservable and so we proxy for effort in two ways.\(^9\) First, we include primitive factors that influence an analyst’s cost of effort, and expect accuracy to be increasing in each of the following attributes: overall and firm-specific experience (\( T_{\text{Exper}}_R \) and \( F_{\text{Exper}}_R \)), and relative resources as proxied by relative broker size (\( \text{Broker}_R \)). We also expect relative accuracy to be decreasing in the analyst’s relative portfolio size (\( \text{Firms}_R \)), because as portfolio size increases analyst effort must be distributed across a larger number of firms. All of the above analyst characteristic variables are computed in relative form as follows: \( \text{Characteristic}_R = \frac{100 - \text{Characteristic}_i_{\text{revrank}}_{i,j,t} - 1}{\text{Follow}_{i,j,t} - 1} \times 100 \), where \( \text{Characteristic} = T_{\text{Exper}}, F_{\text{Exper}}, \text{Broker}, \) and \( \text{Firms} \). \( \text{Characteristic}_i_{\text{revrank}} \) is the reverse ranking of each characteristic yielding higher ranks for higher values on each characteristic. \( \text{Characteristic}_R \), like relative accuracy, ranges from 0 to 100 and captures the extent to which an analyst differs on these characteristics relative to other analysts following the same firm.

\(^9\) While we can observe which analysts actually asked a question, we cannot observe which analysts exerted effort to enter the question queue. Conditioning the sample on only those analysts who entered the question queue would be the ideal research design, because being in the queue would suggest that the analyst was likely attentive to the conference call discussion and interested in obtaining information from the manager. In our sample, we treat analysts who potentially entered the question queue but never got to ask questions as nonparticipating. This misclassification, if anything, would bias against finding evidence in support of our hypotheses.
Second, we include two output measures that capture effort, both of which are expected to be positively related to relative accuracy. In particular, we include the relative forecasting frequency of the analyst during the year prior to the quarter $t$ earnings announcement ($ForFreq_R$) and the relative accuracy ($ACC_{-R_{t,i}^{pre}}$) of the analyst’s last forecast of annual earnings issued immediately before the quarter $t$ earnings announcement. Both measures proxy for how relatively active and accurate the analyst has been in covering the stock prior to the earnings announcement.

We also include a relative measure of the distance from the earnings forecast issued immediately after the conference call ($Horizon_{-R_{post}}$). Forecasts with shorter horizons have the advantage of incorporating more information about upcoming earnings (including the information contained in the forecasts of other analysts) than forecasts issued at longer horizons. We predict a negative association between relative horizon and relative accuracy.

Finally, we include a proxy for analyst competition ($LnFollow$) that serves to control for measurement error in our relative analyst measures for firms with lower levels of analyst following (Hong et al. 2000; Ke and Yu 2006). Note that we do not include measures of bias in earnings forecasts issued prior to the conference call. The literature commonly measures bias in preceding forecasts as a predictor of future forecast accuracy under the notion that bias proxies for access to management (Ke and Yu 2006) and facilitates conference call access (Libby et al. 2008). We measure the intended outcome of such bias – management access via conference call participation – directly via the variable $Participate$, which would make the inclusion of prior forecast bias redundant.\textsuperscript{10}

\textsuperscript{10} Chen and Matsumoto (2006) report that relative forecast accuracy of analysts issuing more favorable recommendations is greater than that for analyst issuing less favorable recommendations. In their paper, the favorableness of analyst recommendations is a proxy for management access. We do not include the favorableness
We also refrain from including other characteristics of the earnings forecast issued immediately after the conference call, such as boldness (Gleason and Lee 2003; Chen and Jiang 2005; Clement and Tse 2006). Boldness is commonly attributed to the possession of superior private information. If conference call participation helps generate this superior private information, including boldness as an explanatory factor would have the effect of controlling away the effect we are attempting to examine.11

Our changes analysis estimates the association between changes in relative forecast accuracy and changes in conference call participation using the following pooled cross-sectional OLS model with standard errors clustered by analyst:

\[
\Delta \text{ACC}_R_{i,j,t} = \alpha_0 + \alpha_1 \Delta \text{Participate}_{i,j,t} + \alpha_2 \Delta \text{Horizon}_R_{i,j,t} + \mu_{i,j,t}
\]

(1b)

where \(\Delta \text{ACC}_R_{i,j,t} = \text{ACC}_R_{i,j,t}^{\text{post}} - \text{ACC}_R_{i,j,t}^{\text{pre}}\), \(\Delta \text{Participate}_{i,j,t} = \text{Participate}_{i,j,t} - \text{Participate}_{i,j,t-1}\), and \(\Delta \text{Horizon}_R_{i,j,t} = \text{Horizon}_R_{i,j,t}^{\text{post}} - \text{Horizon}_R_{i,j,t}^{\text{pre}}\). The dependent variable \(\Delta \text{ACC}_R\) reflects the change in the relative forecast accuracy for forecasts of annual earnings that straddle the conference call. \(\Delta \text{Participate}\) reflects the change in access to management, which is only defined for analysts with available data for consecutive conference calls. H1a predicts that more (less) access will yield increases (decreases) to relative accuracy, implying \(\alpha_1 > 0\). \(\Delta \text{Horizon}\) reflects the change in the relative time span in between the annual forecasts that straddle the conference call. Less negative values of \(\Delta \text{Horizon}\) imply shorter time span in between forecasts, which in turn implies smaller increases in accuracy due to the arrival of information (i.e. \(\alpha_2 < 0\)).

The remaining analyst specific factors are expected to be constant during the period between the

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11 Including the boldness of analyst forecasts as defined in Ke and Yu (2006) in our empirical models does not impact our inferences.
last forecast prior to the conference call and the first forecast after the conference all. As such, those factors are not included in equation (1b). The changes specification helps mitigate the potential for constant, unmeasurable effects from confounding the association between relative forecast accuracy and conference call participation.

3.2.2. Timeliness of annual earnings forecasts

We now turn to a levels analysis of H1b to investigate whether participating analysts issue more timely forecasts. Empirically, we model the duration to forecast as the number of calendar days between quarter t’s earnings announcement date and the date the analyst provides an earnings forecast to I/B/E/S. We employ a Cox proportional hazard estimation with the hazard rate at time t is defined as:

\[ h(t) = \frac{\text{probability of failing between times } t \text{ and } t + \delta}{(\delta)(\text{probability of failing after time } t)} \]

We define the hazard rate as a function of the baseline hazard \( h_0 \) at time t and the effects of the following explanatory variables’ hazard rate at time t as follows, with standard errors clustered by analyst:

\[
h(t) = h_0(t) \exp(\delta_0) + \delta_1 \text{Participate}_{i,j,t} + \delta_2 F_{\text{Exper}}_{R_{i,j,t}} + \delta_3 T_{\text{Exper}}_{R_{i,j,t}} + \delta_4 \ln \text{Follow}_{i,j,t} + \delta_5 \text{Firms}_{R_{i,j,t}} + \delta_6 \text{Broker}_{R_{i,j,t}} + \delta_7 \text{Freq}_{R_{i,j,t}} + \delta_8 ACC_{R_{i,j,t}}^{\text{pre}} + \mu_{i,j,t} \quad (2a)
\]

If conference call participation facilitates faster issuance of information to clients, we expect \( \delta_1 > 0 \). A positive coefficient estimate corresponds with a higher (i.e., more rapid) hazard rate, which would indicate quicker revision of the forecast for participating analysts relative to nonparticipating analysts. We include the same effort proxies from the relative accuracy model because analysts who put forth more effort are both more likely to participate in a conference call and revise their forecasts earlier, with one exception. We no longer include the relative forecast
horizon of the first forecast issued after the conference call as an explanatory variable. Horizon is a function of the time of the first earnings forecast issued after the conference call, which is the duration we are modeling in equation (2a).

Our changes specification models the change in the time it takes an analyst to issue an annual earnings forecast after consecutive conference calls as follows:

$$\Delta Delay_{i,j,t} = \gamma_0 + \gamma_1 \Delta Participate_{i,j,t} + \eta_{i,j,t}$$

(2b)

where $\Delta Delay_{i,j,t} = Delay_{i,j,t} - Delay_{i,j,t-1}$, where $Delay_{i,j,t}$ equals the number of days elapsed between firm $j$’s quarter $t$ earnings announcement and analyst $i$’s first subsequent forecast of annual earnings, and $Delay_{i,j,t-1}$ is the number of days that elapsed between analyst $i$’s first forecast of annual earnings after firm $j$’s quarter $t-1$ earnings announcement. $\Delta Participate$ is as defined previously. As with the changes specification for forecast accuracy (equation 1b) we do not include other analyst or firm specific variables. If increased (decreased) access to management during the conference call decreases (increases) the time-to-market of an annual earnings forecast as H1b predicts, we expect $\gamma_1$ to be negative.

4.0 Results

4.1 Descriptive Statistics and Univariate Results

Panel A of Table 1 provides descriptive statistics for our sample. To facilitate interpretation we provide raw values in addition to the relative measures used in our empirical models. The median analyst in our sample has five years of overall experience, covers ten firms, has two years experience on firms covered, and issues five annual forecasts over the one calendar year leading up to the conference call. The median brokerage size is 53 analysts, which is much larger than the average brokerage size reported in the extant literature (Clement and Tse, 2003; Clement and Tse 2005). This reflects our conditioning the sample on very active analysts, which
tend to be hired by larger brokerages. Conference call participation occurs for 47% of our sample analyst firm quarter observations.

Panel B of Table 1 reveals that our 1,919 sample firms followed closely mimic the population of Compustat in terms of industry concentration. Panel C of Table 1 reveals the distribution of our 8,516 earnings conference calls by calendar quarter. The number of conference calls examined in our sample grows from Q1 of 2002 through Q3 of 2003, leveling off at roughly 850 conference calls each calendar quarter thereafter. The number of calls grows initially as the StreetEvents database grew in popularity, reaching a steady state in the middle of 2003 (Mayew 2008).

Panel D of Table 1 presents the correlation statistics and initial evidence on our hypotheses. Spearman correlations reveal that analysts who participate deliver annual earnings forecasts that are both more timely and more accurate ($\rho(ACC_{R^{post}}, Participate) = 0.01$, $p<0.01$); $\rho(DELAY, Participate) = -0.06$, $p<0.01$). While suggestive, using these correlations to draw conclusions would be premature because a number of other analyst attributes are associated with conference call participation that have been shown to also influence the accuracy and timeliness of earnings forecasts. In particular, Spearman correlations also reveal that participating analysts have relatively more overall and firm experience, cover relatively more firms, work for relatively larger brokerages, and issue relatively more forecasts on the firms they cover. In our multivariate analysis that follows, we explicitly incorporate controls for these factors in our empirical design.

### 4.2 Multivariate Results

Our multivariate analysis of forecast accuracy is presented in Table 2. Consistent with H1a, Panel A of Table 2 reveals that analysts who participate in the conference call provide
significantly more accurate forecasts relative to other analysts following the firm

\( \text{Participate} = 0.524, p<0.01 \). This result obtains after controlling for other known determinants of relative forecast accuracy. The control variables, when significant, behave as predicted. As expected and shown in prior literature (Clement 1999; Brown 2001; Brown and Mohd 2003), the relative accuracy of the analyst immediately prior to the conference call and the relative horizon of the earnings forecast are the most potent predictors of relative forecast accuracy

\( \text{Acc}_\text{pre} = 0.373, p<0.01; \text{Horizon}_\text{post} = -0.347, p<0.01 \). Analysts who follow relatively more firms (work for larger brokerages) are less (more) accurate (Clement and Tse 2003).\(^{12}\)

The changes analysis reported in Panel B of Table 2 buttresses our findings in Panel A. The number of observations used for estimation in Panel B is smaller than those used in Panel A because we require the same analyst coverage on consecutive conference calls in order to construct our change variables.\(^{13}\) As predicted, we find that changes in conference call participation are positively and significantly associated with changes in relative forecast accuracy \( \Delta \text{Participate} = 0.775, p = 0.019 \). The coefficient on the change in relative horizon is significantly negative \( \Delta \text{Horizon}_R = -0.113, p<0.001 \), as expected.

Assuming we have controlled sufficiently for analyst effort, the results thus far suggest analysts who are allowed to participate in conference calls provide more accurate earnings forecasts. These results are consistent with Chen and Matsumoto’s (2006) evidence from the pre-Regulation FD era that access to management improves the forecast accuracy of financial

\(^{12}\) An alternative explanation for these results is that \text{Participate} simply proxies for analysts who issue walkdown forecasts of annual earnings (Richardson et al. 2004; Ke and Yu 2006). If analysts walkdown their annual forecasts, consecutive annual forecasts made early in the year will become consistently more accurate, and at some point become consistently less accurate as the forecasts move from optimistic to pessimistic. To rule out this explanation, we measure whether each analyst during a fiscal year walks down annual earnings forecasts in perfect foresight. That is, we observe the first forecast and last forecast of annual earnings for a given fiscal year for each firm and create an indicator variable that equals one if the first (last) forecast is optimistic (pessimistic) relative to reported earnings. Including this indicator variable does not qualitatively change the inferences.

\(^{13}\) Estimating our levels analysis with the smaller number of observations used in the changes analysis yields qualitatively similar results to those presented in Panel A of Table 2.
analysts. However, evidence from our post FD sample suggests the economic significance is not very large. Recall that relative accuracy is bounded between 1 and 100. Evidence from the levels (changes) specification suggest that participation improves relative accuracy by only 0.524 (0.775) units, which is quite small.

Despite the small magnitude it would be premature to conclude that the accuracy difference associated with conference call participation is not economically meaningful, for at least two reasons. First, this estimate is likely a lower bound. We can only measure differential accuracy effects for analysts who continue to follow the firm. Analysts who know they are likely to be denied participation (such as those analysts with unfavorable views of the firm) may drop coverage and therefore not show up in our sample (McNichols and O’Brien 1997, Mayew 2008). Second, the economic rewards to an analyst from their clients for even a small difference in accuracy may be large when coupled with how quickly an analyst can provide the forecast to the marketplace. That is, we cannot draw conclusions on the economic impact of accuracy without also considering the timeliness with which such an incrementally accurate forecast is delivered.

We now turn to our assessment of forecast timeliness. Panel A of Table 3 presents results from the hazard model specified in equation (2a). The coefficient on Participate is significantly greater than zero ($\delta_1 = 0.052, p<0.001$), implying that participating analysts provide their forecasts to the market more quickly than nonparticipating analysts. Using hazard ratios to describe the economic intuition, our results indicate that, conditional on not having provided an earnings forecast at time $t$, participating analysts are 5.4 percent more likely to provide a forecast at time $t+\delta$ than nonparticipating analysts (hazard ratio is 1.054).

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14 If analysts had unlimited flexibility in choosing their portfolio, they could potentially only follow firms where they would be allowed to participate in the conference call. However, as a practical matter, analysts generally are industry experts who cannot avoid covering certain “bellwether” firms in the industry (Graham et al. 2005).
In terms of control variables, not surprisingly, relatively more accurate analysts immediately preceding the call, analysts working for relatively larger brokerages, and analysts who forecast more frequently all deliver forecasts significantly more quickly to the market. The positive and significant coefficient on $\text{LnFollow}$ is consistent with analysts providing more timely forecasts when the firm has a rich information environment as well as situations where analysts face stiffer competition from other analysts. Surprisingly, analysts with relatively more firm experience and who follow relatively fewer firms deliver forecasts to the market more slowly, after controlling for other factors. However, if heightened focus on an individual firm proxies for analysts with higher ability to learn about the firm, these results are in fact consistent with Guttman (2009), who shows analytically that analysts with higher learning ability will forecast earlier.

Although an advantage of the Cox proportional hazard method of duration analysis is that it is insensitive to the specification of a functional form for the baseline hazard function, assumptions underpinning hazard models estimation may be violated. Further, like the levels model estimated for relative forecast accuracy, correlated omitted variables continue to be concern. As such, we turn to Panel B of Table 3 where we estimate the change, across consecutive conference calls, in the delay between forecast issuance and the earnings announcement.\(^\text{15}\) We find that changes in participation reduces the delay in forecast issuance ($\gamma_1 = -0.827, p=0.035$). This implies that analysts who gained (lost) participation in the conference call deliver their forecasts to the market 0.82 days faster (slower). Given the changes in $\text{Delay}$

\(^{15}\)While hazard models are most appropriate for modeling the amount of time that passes between events, in unreported analysis we also use OLS to estimate the relative delay in the initial forecast of analysts after the conference call as a function of the same determinants in the hazard model. We find negative and significant coefficient on $\text{Participate}$ (coefficient = -1.433, \(p<0.001\)), consistent with participating analysts providing a forecast to the market with relatively less delay than nonparticipating analysts. We also model changes in relative delay as a function of changes in conference call participation and observe a coefficient on $\Delta \text{Participate}$ (coefficient = -1.919, \(p<0.001\)), consistent with increased (decreased) access to management shortening (lengthening) the relative time it takes to issue an earnings forecast.
are measured over consecutive quarterly conference calls, the exclusion of other analyst, broker and firm specific characteristics is appropriate since it is unlikely such characteristics vary in during the 90 days between consecutive earnings conference calls.

In economic terms, 0.82 days equates to roughly 19.68 hours, which anecdotally represents a significant advantage. When discussing the time delay managers can impose on analysts by not answering their questions, Lowengard (2006) states: “for an analyst looking to put out a fast note, four hours may as well be 400.” Additionally, our confidential review of a policies and procedures manual from one large global investment banking firm noted the importance of preparing an analysis of a firm’s earnings as quickly as possible after the earnings conference call with the objective of being the first to notify clients, relative to other analysts. We also reiterate that this estimate of time delay likely represents a lower bound on the effects of conference call participation.

To summarize, the results thus far provide evidence consistent with analysts deriving private benefits from conference call participation. In particular, both levels and changes models provide statistical evidence that participating analysts deliver more “useful and timely” information products to their clients, as evidenced by the accuracy and timeliness of their earnings forecasts. This finding is in contrast with the evidence in prior literature that analysts, on average, trade off accuracy and timeliness when making a forecast (Schipper 1991; Brown and Mohd, 2003). Our results imply that participating analysts face less of a trade off when compared to the nonparticipating analyst since participating analyst forecasts are both more timely and more accurate. This result is also consistent with the theoretical prediction in Guttman (2009) that analysts with higher precision of private information will forecast earlier.
5.0 Robustness and Additional Analyses

5.1 Self Selection and Propensity Score Matching

A limitation of the regression approach to draw inferences about the benefits to conference call participation is that it assumes a linear function form. In addition, participation in a conference call is not random (Mayew 2008). Although we control for other factors that determine conference call participation in the regression specification, it may not completely eliminate potential sample selection bias.\textsuperscript{16} The changes specification partially addresses this issue but imposes an assumption that the factors that determine participation are constant across time.

To mitigate selection bias and examine whether the participation (treatment) effect is robust, we use a propensity score matching procedure (Rosenbaum and Rubin 1983) where we identify a matched set of analysts who did not participate in a conference call but who would have been otherwise allowed to participate in a conference call (i.e., would have fallen under the treatment group) given observable characteristics. Although there are several versions of the matching algorithm in the literature, we use a simple nearest-match method. This matching procedure involves two steps. First, we determine a propensity score for each analyst which is the conditional probability of receiving the treatment effect (i.e., the probability that an analyst gets to participate) given a set of observable characteristics that determine participation. That is, we obtain the propensity score by estimating a logistic regression using the entire sample of participating (treatment) and nonparticipating (control) analysts. Second, for each of the participating analysts we identify a nonparticipating analyst with the closest match, without

\textsuperscript{16} Mayew (2008) models the probability that an analyst asks a question on the conference call. The ideal selection model would model the choice by analysts to enter the question queue of the conference call. After controlling for analyst self-selection into the question queue, analysts allowed to ask questions would clearly be solely a function of managerial choice, and we would proceed to examine differences in the characteristics of analyst outputs. Unfortunately, the question queue is unobservable making such a specification impossible.
replacement, in terms of the propensity score. To ensure comparability between the treatment and the control groups, we drop observations where we are unable to find a reasonable nonparticipating analyst match for a participating analyst, i.e., where the difference in propensity score is more than 0.01.\textsuperscript{17}

Following Mayew (2008) we estimate the following pooled logistic regression to determine the conditional probability of participation by an analyst at a firm’s quarterly conference call:

\[
\text{Participate}_{i,j,t} = \beta_0 + \beta_1 \text{SBuy}_{i,j,t} + \beta_2 \text{Buy}_{i,j,t} + \beta_3 \text{Sell}_{i,j,t} + \beta_4 \text{SSell}_{i,j,t} + \beta_5 \text{Qamin}_{i,j,t} \\
+ \beta_6 \text{LnFollow}_{i,j,t} + \beta_7 \text{AllStar}_{i,j,t} + \beta_8 \text{ACC} \_R_{\text{pre}}\text{R}_{i,j,t} + \beta_9 \text{F} \_\text{Exper} \_R_{i,j,t} \\
+ \beta_{10} \text{T} \_\text{Exper} \_R_{i,j,t} + \beta_{11} \text{Inds} \_R_{i,j,t} + \beta_{12} \text{ForFreq} \_R_{i,j,t} + \beta_{13} \text{Broker} \_R_{i,j,t} \\
+ \beta_{14} \text{Firms} \_R_{i,j,t} + \beta_{15} \text{CCuser}_{i,j,t} + \beta_{16} \text{PriorParticipate}_{i,j,t} \\
+ \beta_{17} \text{RecHorizon}_{i,j,t} + \nu_{i,j,t}. \tag{3}
\]

The dependent variable, \(\text{Participate}_{i,j,t}\), as defined earlier, is an indicator variable that represents whether the analyst asked a question during the conference call. \(\text{SBuy, Buy, Sell, and SSell}\) are indicator variables that capture the analyst’s most recent outstanding stock recommendation prior to the conference call. \(\text{Qamin}\) is the length of the question and answer portion of the call in minutes, where minutes are derived from total word count of the conference-call transcript at 150 words per minute. \(\text{LnFollow, ACC} \_R_{\text{pre}}, \text{F} \_\text{Exper} \_R, \text{T} \_\text{Exper} \_R, \text{ForFreq} \_R, \text{Broker} \_R, \text{and Firms} \_R\) are defined as in equation (1a). \(\text{AllStar}\) indicates whether the analyst was included on any of the Institutional Investor Research All-American teams in the most recent prior year, \(\text{Inds} \_R\) is the analyst’s relative industry coverage, and \(\text{CCuser}\) is the total number of conference calls (excluding firm \(j\)) in which analyst \(i\) participated during the calendar quarter containing fiscal quarter \(t\) for firm \(j\). Finally, \(\text{PriorParticipate}\) indicates whether the analyst asked a question on any of firm \(j\)’s prior

\textsuperscript{17}Relaxing the restriction of the difference in propensity score from .01 to .05 does not impact our inferences.
conference calls in the sample, and $RecHorizon$ measures the number of days between the conference call date and the date of the analyst’s most recent stock recommendation.

Panel A of Table 4 presents the results of estimating equation (3). All independent variables are statistically significant in the same direction as documented in Mayew (2008), with the exception that prior accuracy is positive but not statistically significant, while relative broker size is positive and statistically significant. The overall pseudo R² is 14.2%, which is of comparable magnitude to the 20.0% documented in Mayew (2008). Collectively, the behavior of the independent variables and model fit suggest we are able to successfully replicate the selection model of Mayew (2008) for our sample.

Using the coefficients from equation (3), we compute the propensity score for each observation as the predicted probability that an analyst participates in the conference call. This forms the basis for constructing matched pairs using the nearest-match method described earlier. Because we restrict our sample to pairs with a near perfect match on propensity scores (where the difference in propensity scores is less than 0.01), we increase the likelihood of covariate balance, i.e., the similarity in the distribution of the treatment and the propensity score matched control samples. It is not surprising that the mean (median) of the propensity scores for the treatment and control samples is not statistically different (see Panel B of Table 4). To further assess covariate balance we test whether the means (median) of the independent variables in equation (3) are different between the treatment and control samples. With the exception of $LnFollow$ and $Firms_R$, we observe no statistical differences across the samples (results not reported) suggesting that our matching scheme was reasonably successful in ensuring covariate balance.
Comparing the main variables of interest, forecast accuracy ($ACC_{R^{post}}$) and timeliness ($DELAY$) across the two samples, Panel B of Table 4 reveals that participating analysts are both more accurate and timely than nonparticipating analysts. The mean differences are also consistent with results documented in Tables 2 and 3. With respect to forecast accuracy, participating analysts are statistically better than nonparticipating analysts by 0.696 units ($p = 0.05$), which is comparable to the 0.775 units reported in Panel B of Table 2. With respect to timeliness, participating analysts deliver forecasts statistically faster by 0.983 days ($p<0.01$) which is comparable to 0.827 days reported in Panel B of Table 3. Collectively, the results in Table 4 indicate that our findings are quite robust.

5.2 Analyst effort as a competing explanation

In our research design, we have attempted to rule out the lack of effort as a competing explanation in three ways. First, our sample selection requires that all analysts issue a forecast within a 90 day period both before and after the conference call. This ensures that we have isolated analysts with significant vested interest in following the firm and provide earnings forecasts. Second, we include several proxy variables to capture analyst effort in our levels analysis. Third, we perform corroborating propensity score matched pair analysis and changes analysis which effectively match on effort characteristics or difference them away. Despite these attempts, analyst effort is not observable and as such, the possibility remains that some analysts simply may not have put forth the effort to ask a question on the conference call.

Since we cannot completely rule out effort, we conduct a different test. Specifically, we introduce an analysis of subsequent recommendation revision activity that can both rule out effort as a competing explanation and provide additional insights on the implications of conference call participation. If analysts receive private information benefits from participating
on conference calls, managers will not rationally provide such benefits for free. Chen and Matsumoto (2006) and Mayew (2008) provide evidence consistent with favorable stock recommendations being one currency to obtain such benefits.\textsuperscript{18} Under this economic setting, analyst participation becomes an observable proxy for analysts who have received a favor from management and from whom management may expect continued reciprocity in the form of maintaining favorable recommendations.

O’Brien et al. (2005) documents that analysts with incentives to maintain relationships that hinge on the favorability of stock recommendations have incentives to accelerate (delay) the reflection of good (bad) news into their stock recommendations. If participating analysts in fact are receiving private information benefits from management access during conference calls, we should also observe recommendation activity that responds to earnings news in a way that is pleasing to management. Stated formally:

H2a: Participating analysts are less likely to downgrade stock recommendations in the presence of bad news than nonparticipating analysts.

H2b: Participating analysts are more likely to upgrade stock recommendations in the presence of good news than nonparticipating analysts.

Note that if participation on a conference call captured only effort and is not an indication of some private benefit received by the analyst, we would expect participating analysts to update their recommendations with a higher likelihood regardless of the news. That is, participating analysts would be more likely to upgrade in the presence of good news \textit{and} more likely to downgrade in the presence of bad news.

\textsuperscript{18} An alternative currency purported to be used by analysts to curry favor with management is the walkdown forecast (Libby et al. 2008; Ke and Yu 2006). However, to identify whether an annual forecast issued after a conference call is being walked down appropriately, the researcher needs to make assumptions about when during the fiscal year a manager would prefer a forecast to turn from optimistic to pessimistic. Given the ambiguity regarding the evolution of a walkdown forecast, we instead examine stock recommendations.
To test whether analysts differentially incorporate bad (good) news into their stock recommendations, we model the probability that an analyst downgrades (upgrades) the firm’s shares over the 90 days subsequent to the earnings announcement as a function of whether the analyst participated on the conference call using the following logistic regression specification:

\[
\Pr(\text{Downgrade}_{i,j,t+1}|FE_{i,j,t}<0) = \beta_0 + \beta_1 \text{Participate}_{i,j,t} + \beta_2 \text{SBuy}_{i,j,t} + \beta_3 \text{Buy}_{i,j,t} + \beta_4 \text{Hold}_{i,j,t} + \beta_5 \text{Sell}_{i,j,t} + \epsilon_{i,j,t}
\]

\[
\Pr(\text{Upgrade}_{i,j,t+1}|FE_{i,j,t}>0) = \alpha_0 + \alpha_1 \text{Participate}_{i,j,t} + \alpha_2 \text{Buy}_{i,j,t} + \alpha_3 \text{Hold}_{i,j,t} + \alpha_4 \text{Sell}_{i,j,t} + \alpha_5 \text{SSell}_{i,j,t} + \nu_{i,j,t}
\]

The dependent variable in model 3a (3b) takes on a value of 1 if the analyst downgraded (upgraded) a firm’s stock in the presence of a bad (good) news during the 90 days subsequent to the earnings announcement at quarter \(t\), and zero otherwise. We choose a 90 day period to be consistent with our earnings forecast tests. Because we can measure each individual analyst’s expectation of quarter \(t\)’s earnings we are able to measure whether the quarterly earnings realization was good or bad news from the perspective of each individual analyst. We therefore operationalize analyst specific news via each individual analyst’s forecast error, \(FE_{i,j,t}\), defined as the price scaled split-unadjusted I/B/E/S actual earnings per share for quarter \(t\) minus the last split-unadjusted forecast for quarter \(t\)’s earnings issued by analyst \(i\) covering firm \(j\). H2a and H2b predict \(\beta_1\) to be negative and \(\alpha_1\) to be positive.

Each model controls for the existing stock recommendation, as the probability of a downgrade increases as the existing stock recommendation becomes more favorable (O’Brien et al. 2005). Naturally, model 3a (3b) excludes observations where the analyst recommendation
was a strong sell (strong buy) since upgrades (downgrades) are not possible from such recommendation levels.19

Panel A of Table 5 provides descriptive evidence for both the good news and bad news analyst forecast error samples. We find that the distribution of price scaled analyst specific earnings surprises to be virtually identical in both subsamples, with a mean of 0.012 (-0.013) and standard deviation of 0.544 (0.494) for the good (bad) news subsamples. This suggests the news received by the analysts in each subsample is not likely to differ on dimensions such as the transitory nature of the surprise. Further, we find that conference call participation is also virtually identical, with 46.6% (46.5%) participation percentages in the good (bad) news subsamples, implying that participation is not systematically related with whether the analyst is positively or negatively surprised by reported earnings. Finally, we observe that analysts in the good news sample have slightly more unfavorable stock recommendations prior to observing the good news, with an average of 2.82, compared with an average of 2.38 for the bad news sample.20

Turning to our recommendation revision tests, in Panel B of Table 5 we find the coefficient on Participate to be negative and significant ($\beta_1 = -0.145, p<0.01$). This implies that, conditional on receiving bad news, and controlling for the existing recommendation level, analysts who participate are significantly less likely to downgrade the firm’s stock over the subsequent 90 days. Panel C of Table 5 shows the opposite, as predicted. Conditional on receiving good news, analysts who participate are more likely to upgrade the firm’s shares than

19 To ensure our tests compare analysts who continue to follow the firm after the earnings news is received, we include only analysts who revise their stock recommendation on the firm at least once in the year following the earnings announcement.
20 We retain the I/B/E/S coding methodology such that more favorable recommendations receive smaller values (strong sell as 5, sell as 4, hold as 3, buy as 2 and strong buy as 1).
An analysis of predicted probabilities (not tabulated) reveals that participating analysts are, on average, 11 percent less likely to downgrade firms that miss their earnings forecasts and 10 percent more likely to upgrade firms that beat their earnings forecasts.

Together, these recommendation revision results are more consistent with participation yielding some private benefit for the analyst rather than participation simply proxying for differential analyst effort. Aside from ruling out effort as an alternative explanation, these results extend the extant literature in two important ways. First, O’Brien et al. (2005) show analysts with investment banking ties asymmetrically impound good and bad news. The change in regulation through the Global Settlement in April of 2003 was meant to remove this investment banking conflict. Our study, conducted in periods primarily subsequent to the Global Settlement, suggests an additional conflict that may require regulatory attention.

Second, this result builds on Mayew (2008) by showing that analyst recommendation activity after the conference call is also associated with whether the analyst is allowed to participate. Mayew (2008) finds that analysts who issue more favorable stock recommendations prior to the conference call are more likely to participate. However, his result cannot discriminate between information benefits and management preferring to discuss the firm’s prospects with analysts who share a similar favorable view of the firm. Our results suggest the association in Mayew (2008) is more consistent with the private information benefits explanation.

21 Note that if analysts systematically bias their earnings forecasts downward (Ke and Yu 2006; Libby et al. 2008), positive analyst forecast errors may not represent favorable news about the firm. This would bias against finding results for H2(b).

22 An alternative way to investigate whether the analyst receives an information benefit is to observe whether the stock market reacts differentially to initial earnings forecasts issued by participating analysts relative to analysts who do not participate. This test is difficult to execute because the average difference in timeliness is less than one day. Thus, the use of daily firm level stock returns would be confounded with the market reaction to both the participating and nonparticipating analysts.
5.3 Other Private Benefits to Participation

Is private information the only benefit? The preceding analysis provides evidence consistent with analysts receiving private information benefits. But it does not preclude the possibility that participation provides other benefits as discussed in Libby et al. (2008). For example, analyst clients may simply believe the information from analysts who they can “see working” by asking questions on the conference call may heighten their view of the analyst, and in turn rate the analyst more favorably. If conference call participation provides labor market benefits more generally than information benefits, the participating analyst should in turn enjoy more favorable career outcomes, all else equal. This leads to the following hypothesis:

H3: Analyst turnover is likely to be higher for nonparticipating analysts than participating analysts, after controlling for information benefits.

To investigate the extent to which conference call participation plays a role in the career outcomes of analysts, we estimate the following logistic regression model of the probability of analyst turnover in the subsequent year, with standard errors clustered by analyst:

\[
\Pr(A_{\text{Turnover}_{i,t+1}}) = \delta_0 + \delta_1 A_{\text{Participate}_{i,t}} + \delta_2 A_{\text{ACC}_{R_{i,t}}} \\
+ \delta_3 \ln(A_{\text{Delay}_{i,t}}) + \delta_4 \ln(A_{\text{Total Exper}_{i,t}}) \\
+ \delta_5 \ln(A_{\text{ForFreq}_{i,t}}) + \omega_i, \tag{4}
\]

Following prior literature (Hong et al. 2000; Ke and Yu 2006), \( A_{\text{Turnover}} \) is an indicator variable that equals 1 if the analyst moves to a broker employing less than 25 analysts in the year following the annual earnings announcement or is not listed in I/B/E/S at the end of the subsequent year, and zero otherwise. \( A_{\text{Participate}} \) is the ratio of the number of firms in the portfolio where the analyst participated in at least one conference call during the year. We expect \( \delta_1 < 0 \) if participation lowers the probability of analyst turnover.

\( A_{\text{ACC}_{R}} \) is the average (across firms in the analyst’s portfolio) relative accuracy of an analyst’s first forecast of annual earnings after the conference call from the third fiscal quarter.
A_Delay is the average (across firms in the analyst's portfolio) number of days elapsed since the third fiscal quarter earnings conference call and the first annual earnings estimate provided after the third fiscal quarter conference call. A_ACC_R (A_Delay) proxy for information benefits, and we expect that the more accurate (more delay) in forecasting the forecast is, the less (more) likely is the turnover.

A_Total_Exper is the number of years of experience the analyst has. We expect longer serving analysts, who presumably have survived due to their superior ability, to have lower likelihood of turnover. A_ForFreq is the average number of forecasts issued over the analyst’s portfolio during the year. We expect analysts who exert more effort to deliver more forecasts to be less likely to experience an employment separation. The count variables A_Delay, A_Total_Exper, and A_ForFreq are right skewed, so we use the natural logarithm of these variables in our empirical specification.

Panel B of Table 6 presents the empirical results of the relation between analyst turnover and conference call participation. We observe a negative and significant coefficient on A_Participate ($\delta_1 = -0.377, p = 0.060$ two tailed), suggesting participating analysts are less likely to experience a downward employment separation. To assess economic significance, we note that the unconditional turnover rate depicted in Table 6 Panel A is 1.8 percent. Holding all other variables at their means, the predicted turnover probability (untabulated) for analysts participating in a conference call for all firms ($A_Participate = 1$) in their portfolio is 1.5 percent, compared with 2.2 percent for analysts who do not participate in any conference calls during the year for their portfolio ($A_Participate = 0$).
Turning to control variables, analysts with more overall experience are less likely to turnover. However, the remaining control variables do not behave as predicted.\footnote{It is difficult to ascertain why the control variables do not behave as predicted. Two main differences relative to the extant literature examining analyst turnover (Hong and Kubik 2003; Clement and Tse 2005; Ke and Yu 2006) appear to be sample selection and the particular forecast we use to measure accuracy and delay at the analyst level. With respect to the former, our analyst level specification is derived using the observations in our determinant models of accuracy and timeliness, which is conditioned on very active analysts working for large brokerage firms. Second, we measure accuracy and delay at the analyst level using the first annual forecast after 3rd quarter earnings. Commonly, the literature uses the last annual earnings forecast of the year for each firm in an analyst’s portfolio.} The coefficients on analyst forecast accuracy and forecast frequency are positive and not statistically significant. Contrary to expectations, we also observe a statistically negative association between turnover and the delay of the forecast, suggesting that analysts who withhold their forecast longer are less likely to turnover. If participation is in fact capturing information benefits, the coefficients on accuracy and delay represent the impact of accuracy and delay after controlling for the information benefits. The mixed results on the control variables make it difficult to discern whether participation provides benefits over and above information benefits, but it is clear that participation is in fact associated with lower likelihood of employment separation.

Taken together, we find some evidence of labor market benefits, but this exploration is admittedly preliminary. A comprehensive examination of all the benefits associated with conference call participation is beyond the scope of this study. Therefore we leave an investigation of other tangible and intangible benefits to conference call participation to future research.

\textbf{6.0 Conclusion}

This paper investigates whether, post-Reg FD, analysts who ask questions in public earnings conference calls receive private information benefits relative to analysts who do not ask questions. Our evidence suggests that conference call access provides informational benefits to
analysts who ask questions during the calls. After controlling for analyst effort in a levels, changes, and a propensity score matched sample specification, we find that analysts who participate in conference calls issue annual earnings forecasts that are both more accurate and timely than analysts who do not participate in the calls. These results add to the literature documenting that public information can have private information benefits and shed new light on the nature of the benefits of conference call access.

We also investigate whether analysts who participate in conference calls are more (less) likely to incorporate good (bad) news information into their stock recommendations. Consistent with reciprocity for receiving conference call access, we find that analysts who participate in conference calls are more (less) likely to upgrade (downgrade) a firm’s stock recommendation after receiving good (bad) news about the firm over the 90 days subsequent to the earnings announcement. Our study adds to recent evidence that suggests analysts and managers continue to exchange private benefits, even in the post-Reg FD period (Cohen et al. 2008; Westphal and Clement 2008). We believe this information is important to regulators as they evaluate the success of Reg FD in curtailing selective disclosures and consider the costs and benefits of attempting to maintain a level information playing field through further regulation of manager and analyst interactions.

Finally, we document that analysts who participate in conference calls are less likely to experience negative career outcomes (i.e., turnover) in the year after the earnings announcement, incremental to other potential explanatory factors for turnover. This preliminary finding hints at other private benefits to conference call access beyond information benefits, as suggested by Libby et al. (2008). We leave the exploration of such non-information benefits to future research.
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Appendix 1

To illustrate the informational benefits of being able to ask a question on a conference call, we apply the Kim and Verrecchia (1997) framework to the conference call setting. Suppose firm value $V$ is comprised of three components $V_1, V_2$ and $V_3$, such that $V = V_1 + V_2 + V_3$.

Consider a manager with three private, noisy and uncorrelated signals of firm value, $S_1 = V_1 + \varepsilon_1$, $S_2 = V_2 + \varepsilon_2$ and $S_3 = V_3 + \varepsilon_3$, that will be supplied to the market when asked for by analysts during the conference call. Next, introduce three financial analysts, A, B and C, who each uncover noisy private information about the error term in one of the manager’s private signals. We assume that in a competitive environment, analysts collect different private information based on their differential skill and expertise (see Barron et al. 2002 for an example). This assumption of analysts seeking out differential private information is also consistent with strategies that brokerage house employers suggest to prospective sell side analysts. Analyst A (B) [C]’s noisy private information is characterized as $I_A = \varepsilon_1 + \eta_A (I_B = \varepsilon_2 + \eta_B) [I_C = \varepsilon_3 + \eta_C]$. Each analyst’s noisy private information cannot be used in isolation to learn about firm value since they do not contain components of $V$.

Suppose only analyst A and analyst B are allowed to ask questions during the conference call. They will ask questions conditional on their private information, and management will provide public signals $S_1$ and $S_2$. With public signal $S_1$, analyst A can combine the public signal with her own private signal to generate a new private signal about firm value, $Z_{1A}$, where $Z_{1A} = S_1 - I_A = V_1 + \eta_A$. Analyst B cannot generate a new private signal from $S_1$ about firm value because $S_1$ and $I_B$ do not carry a common element to allow combination. Similarly, with $S_2$ analyst B can generate a new private signal but analyst A cannot. Analyst C, who asks no question, generates no information about firm value from either public signal.

24 We attended an information session hosted by the managing director and director of research at a prominent sell-side research firm. The purpose of this information session was to provide an audience of MBA students, many of whom become sell-side analysts, with insights about a career as a sell-side analyst, keys to success, and sources of failure in the profession. The overarching objective of all analysts is client service, with primary interest on institutional investors. Regarding impressing institutional investor clients, the director of research said all analysts had to first “find a niche.” Broadly, “finding a niche” means specializing in economic value-driving aspects of covered firms that would uniquely identify the analyst to institutional clients relative to other analysts. Examples include being a “foreign growth” specialist or a “supply chain” specialist.
Thus, we argue that although questions and answers are both publicly disclosed during conference calls, new unique private signals of value can be generated for the analyst who asks a question. In this way, conference call participation is a means by which analysts can generate an informational advantage over other analysts. Nothing prevents the analyst who does not ask a question from gathering additional private information about the public signal’s error term after the public signal is released. However, private information gathering *ex post* is particularly costly because it takes time and effort. For clients looking to exploit market opportunities, time is of the essence and the value of information provided by analysts is decreasing in time (Lowengard 2006).
Appendix 2
Variable Definitions

Analyst-Firm-Quarter Level Variables

**ACC\_R\_post** is the relative accuracy of analyst $i$'s first forecast of firm $j$'s annual earnings issued after quarter $t$'s earnings announcement. Following Ke and Yu (2006), estimates range between zero and 100: \[ ACC\_R\_post = 100 - \frac{(absFErank\_post - 1)}{(Follow - 1)} \times 100. \]

$absFErank\_post$ is the rank of the absolute forecast error, $FE$, of an analyst $i$'s initial forecast of upcoming annual earnings after the conference call among forecasting analysts. $Follow$ is the number of analysts providing a forecast.

**ACC\_R\_pre** is the relative accuracy of analyst $i$'s last forecast of firm $j$'s annual earnings issued before quarter $t$'s earnings announcement. Following Ke and Yu (2006), estimates range between zero and 100: \[ ACC\_R\_pre = 100 - \frac{(absFErank\_pre - 1)}{(Follow - 1)} \times 100. \]

$absFErank\_pre$ is the rank of the absolute forecast error, $FE$, of an analyst $i$'s last forecast of upcoming annual earnings before the conference call among forecasting analysts. $Follow$ is the number of analysts providing a forecast.

**Broker\_R** is the relative size of the brokerage house employing analyst $i$ at the time of the quarter $t$ earnings announcement, defined as \[ \frac{Broker\_revrank_{i,j,t} - 1}{Follow_{i,j,t} - 1} \times 100, \]
where $Broker\_revrank$ is the reverse ranking of $Broker$.

**Broker** is the number of employees working at the brokerage house as of the most recently completed calendar quarter prior to the conference call date.

**Buy** is an indicator variable that equals 1 if analyst $i$'s recommendation for firm $j$'s stock prior to the quarter $t$ earnings announcement is buy, and zero otherwise.

**CCuser** is the total number of conference calls (excluding firm $j$) in which analyst $i$ participated during the calendar quarter containing fiscal quarter $t$ for firm $j$.

**Delay** is the number of days that elapse between firm $j$'s quarterly earnings announcement and the issuance of analyst $i$'s first one-year-ahead annual earnings forecast subsequent to the conference call.

**Downgrade** is an indicator variable that equals 1 if analyst $i$ downgrades the stock recommendation for firm $j$ in the 90 days subsequent to the quarter $t$ earnings announcement and zero otherwise.

**F\_Exper** is the number of full years of experience analyst $i$ has covering firm $j$, as of quarter $t$.

**F\_Exper\_R** is the relative firm specific experience defined as \[ \frac{F\_Exper\_revrank_{i,j,t} - 1}{Follow_{i,j,t} - 1} \times 100, \]
where $F\_Exper\_revrank$ is the reverse ranking of $F\_Exper$.

**FE** is the difference between the firm's actual reported earnings and analyst $i$'s annual earnings forecast and as obtained from the I/B/E/S unsplitt-adjusted detail file.

**FE\_p** is FE scaled by stock price two days before the quarter $t$ earnings announcement.

**Firms** is the number of firms followed by analyst $i$ at quarter $t$, as measured by the number of firms for which the analyst forecasts provides forecasts for within the sample.

**Firms\_R** is the relative number of firms covered defined as \[ \frac{Firms\_revrank_{i,j,t} - 1}{Follow_{i,j,t} - 1} \times 100, \]
where $Firms\_revrank$ is the reverse ranking of $Firms$.

**ForFreq** is the number of annual earnings forecasts for firm $j$ issued by analyst $i$ in the 12 months prior to the quarter $t$ earnings announcement.
**ForFreq_R** is the relative number of annual earnings forecasts issued defined as
\[ \frac{\text{ForFreq}_{revrank_{i,j,t}} - 1}{\text{Follow}_{i,j,t} - 1} \times 100, \]
where **ForFreq_{revrank}** is the reverse ranking of **ForFreq**.

**Follow** is the number of I/B/E/S sell-side analysts in our sample forecasting annual future earnings for firm \( j \) at quarter \( t \).

**LnFollow** is the natural logarithm of **Follow**.

**Hold** is an indicator variable that equals 1 if analyst \( i \)'s recommendation for firm \( j \)'s stock prior to the quarter \( t \) earnings announcement is hold, and zero otherwise.

**Horizon_{post}** is the number of days between the analyst \( i \)'s first forecast of firm \( j \)'s annual earnings issued after quarter \( t \)'s earnings announcement and the report date of annual earnings.

**Horizon_{R_{post}}** is the relative forecast horizon of analyst \( i \)'s first forecast of firm \( j \)'s annual earnings issued after quarter \( t \)'s earnings announcement defined as
\[ \frac{\text{Horizon}_{post}_{revrank_{i,j,t}} - 1}{\text{Follow}_{i,j,t} - 1} \times 100, \]
where **Horizon_{post}_{revrank}** is the reverse ranking of **Horizon_{post}**.

**Inds** is the number of industries covered by the analyst over the most recently completed calendar year prior to the conference call date.

**Inds_R** is the relative number of industries covered by the analyst over the most recently completed calendar year prior to the conference call date defined as
\[ \frac{\text{Inds}_{revrank_{i,j,t}} - 1}{\text{Follow}_{i,j,t} - 1} \times 100, \]
where **Inds_{revrank}** is the reverse ranking of **Inds**.

**Participate** is an indicator variable that equals 1 if the analyst \( i \) asked a question on firm \( j \)'s quarter \( t \) conference call, and zero otherwise.

**Prior_Participate** is an indicator variable that equals 1 if the analyst was identified as asking a question on any of the firm's prior conference calls in the sample, and 0 otherwise.

**QAmin** is the length of the question and answer portion of the call in minutes, where minutes are derived by converting the total word count of the question and answer session to minutes using a rate of 150 words per minute.

**Rec** is the recommendation level of analyst \( i \)'s recommendation for firm \( j \)'s stock prior to the quarter \( t \) earnings announcement, where strong buy = 1, buy = 2, hold = 3, sell = 4, and strong sell = 5.

**RecHorizon** is the recommendation horizon measured as the number of days between the conference call date and the date of the analyst’s most recent stock recommendation.

**SBuy** is an indicator variable that equals 1 if analyst \( i \)'s recommendation for firm \( j \)'s stock prior to the quarter \( t \) earnings announcement is strong buy, and zero otherwise.

**Sell** is an indicator variable that equals 1 if analyst \( i \)'s recommendation for firm \( j \)'s stock prior to the quarter \( t \) earnings announcement is sell, and zero otherwise.

**SSell** is an indicator variable that equals 1 if analyst \( i \)'s recommendation for firm \( j \)'s stock prior to the quarter \( t \) earnings announcement is strong sell, and zero otherwise.

**T_Exper** is the number of full years of experience analyst \( i \) has covering any firm on I/B/E/S as of quarter \( t \).

**T_Exper_R** is the relative total experience defined as\[ 100 - \frac{\text{T_Exper}_{revrank_{i,j,t}} - 1}{\text{Follow}_{i,j,t} - 1} \times 100, \]
where **T_Exper_{revrank}** is the reverse ranking of **T_Exper**.
Upgrade is an indicator variable that equals 1 if analyst $i$ upgrades the stock recommendation for firm $j$ in the 90 days subsequent to the quarter $t$ earnings announcement and zero otherwise.

**Analyst-Year Level Variables**

A_ACC_R is the average $ACC_R^{post}$ for analyst $i$’s initial annual earnings forecast issued after the Q3 earnings conference calls in year $y$, across all firms in her portfolio.

A_Delay is the average Delay for analyst $i$’s initial annual earnings forecast issued after the Q3 earnings conference calls in year $y$, across all firms in her portfolio.

A_ForFreq is the average number of forecasts issued over the analyst’s portfolio during year $y$.

A_Participate is the proportion of firms in analyst $i$’s portfolio in which the analyst asked a question on at least one quarterly earnings conference call during year $y$.

A_Total_Exper_R is the number of full years of experience analyst $i$ has covering any firm in I/B/E/S as of the beginning of year $y$.

A_Turnover is an indicator variable that equals 1 if the analyst moves to a broker employing less than 25 analysts in the year following the annual earnings announcement or is not listed in I/B/E/S at the end of the subsequent year, and zero otherwise.

AllStar is an indicator variable that equals 1 if the analyst made any of the Institutional Investor Research All-American teams as of the most recent prior year, and 0 otherwise.
Table 1
Descriptive Statistics

Panel A: Univariate statistics for 57,443 analyst firm quarters

<table>
<thead>
<tr>
<th>Variable</th>
<th>Mean</th>
<th>Median</th>
<th>Std Dev</th>
<th>Min</th>
<th>Max</th>
</tr>
</thead>
<tbody>
<tr>
<td>Delay</td>
<td>13.48</td>
<td>1.00</td>
<td>24.49</td>
<td>1.00</td>
<td>91.00</td>
</tr>
<tr>
<td>Horizon(\text{post})</td>
<td>215.44</td>
<td>195.00</td>
<td>100.17</td>
<td>1.00</td>
<td>425.00</td>
</tr>
<tr>
<td>Horizon(R)(\text{post})</td>
<td>46.24</td>
<td>45.28</td>
<td>28.25</td>
<td>0.00</td>
<td>100.00</td>
</tr>
<tr>
<td>F_Exper(R)</td>
<td>50.97</td>
<td>50.00</td>
<td>28.43</td>
<td>0.00</td>
<td>100.00</td>
</tr>
<tr>
<td>Firms(R)</td>
<td>49.71</td>
<td>50.00</td>
<td>29.42</td>
<td>0.00</td>
<td>100.00</td>
</tr>
<tr>
<td>LnFollow</td>
<td>3.34</td>
<td>3.43</td>
<td>0.78</td>
<td>1.10</td>
<td>4.87</td>
</tr>
<tr>
<td>Broker(R)</td>
<td>49.30</td>
<td>50.00</td>
<td>29.89</td>
<td>0.00</td>
<td>100.00</td>
</tr>
<tr>
<td>T_Exper(R)</td>
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<td>50.00</td>
<td>29.40</td>
<td>0.00</td>
<td>100.00</td>
</tr>
<tr>
<td>ForFreq(R)</td>
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<td>50.00</td>
<td>28.86</td>
<td>0.00</td>
<td>100.00</td>
</tr>
<tr>
<td>Acc(R)(\text{post})</td>
<td>52.74</td>
<td>53.85</td>
<td>29.42</td>
<td>0.00</td>
<td>100.00</td>
</tr>
<tr>
<td>Acc(R)(\text{pre})</td>
<td>52.52</td>
<td>53.33</td>
<td>29.51</td>
<td>0.00</td>
<td>100.00</td>
</tr>
<tr>
<td>F_Exper(rn)</td>
<td>2.82</td>
<td>2.00</td>
<td>3.71</td>
<td>0.00</td>
<td>22.00</td>
</tr>
<tr>
<td>Firms(rn)</td>
<td>10.92</td>
<td>10.00</td>
<td>5.33</td>
<td>1.00</td>
<td>46.00</td>
</tr>
<tr>
<td>Broker(rn)</td>
<td>85.85</td>
<td>53.00</td>
<td>82.02</td>
<td>1.00</td>
<td>393.00</td>
</tr>
<tr>
<td>T_Exper(rn)</td>
<td>6.28</td>
<td>5.00</td>
<td>5.56</td>
<td>0.00</td>
<td>22.00</td>
</tr>
<tr>
<td>ForFreq(rn)</td>
<td>5.13</td>
<td>5.00</td>
<td>3.00</td>
<td>0.00</td>
<td>31.00</td>
</tr>
<tr>
<td>Participate</td>
<td>0.47</td>
<td>0.00</td>
<td>0.50</td>
<td>0.00</td>
<td>1.00</td>
</tr>
</tbody>
</table>
Table 1 (continued)

*Panel B: Comparison of industry composition of 1,919 sample firms and Compustat universe*\(^b\)

<table>
<thead>
<tr>
<th>Industry</th>
<th>Firms</th>
<th>% of Sample</th>
<th>% of Compustat population firm-year observations 2003-2005 in each industry</th>
</tr>
</thead>
<tbody>
<tr>
<td>Food</td>
<td>36</td>
<td>2%</td>
<td>2%</td>
</tr>
<tr>
<td>Mining and Minerals</td>
<td>24</td>
<td>1%</td>
<td>4%</td>
</tr>
<tr>
<td>Oil and Petro Products</td>
<td>92</td>
<td>5%</td>
<td>5%</td>
</tr>
<tr>
<td>Textiles, Apparel &amp; Footware</td>
<td>26</td>
<td>1%</td>
<td>1%</td>
</tr>
<tr>
<td>Consumer Durables</td>
<td>32</td>
<td>2%</td>
<td>2%</td>
</tr>
<tr>
<td>Chemicals</td>
<td>33</td>
<td>2%</td>
<td>1%</td>
</tr>
<tr>
<td>Drugs, Soap, Perfumes, Tobacco</td>
<td>72</td>
<td>4%</td>
<td>4%</td>
</tr>
<tr>
<td>Construction</td>
<td>40</td>
<td>2%</td>
<td>2%</td>
</tr>
<tr>
<td>Steel</td>
<td>24</td>
<td>1%</td>
<td>1%</td>
</tr>
<tr>
<td>Fabricated Products</td>
<td>10</td>
<td>1%</td>
<td>1%</td>
</tr>
<tr>
<td>Machinery and Business Equipment</td>
<td>292</td>
<td>15%</td>
<td>9%</td>
</tr>
<tr>
<td>Automobiles</td>
<td>24</td>
<td>1%</td>
<td>1%</td>
</tr>
<tr>
<td>Transportation</td>
<td>67</td>
<td>4%</td>
<td>3%</td>
</tr>
<tr>
<td>Utilities</td>
<td>46</td>
<td>2%</td>
<td>3%</td>
</tr>
<tr>
<td>Retail Stores</td>
<td>136</td>
<td>7%</td>
<td>4%</td>
</tr>
<tr>
<td>Financial Institutions</td>
<td>268</td>
<td>14%</td>
<td>25%</td>
</tr>
<tr>
<td>Other</td>
<td>697</td>
<td>36%</td>
<td>32%</td>
</tr>
<tr>
<td>Total</td>
<td>1,919</td>
<td>100%</td>
<td>100%</td>
</tr>
</tbody>
</table>
Table 1 (continued)

*Panel C: Frequencies*

<table>
<thead>
<tr>
<th>Unique Firms</th>
<th>1,919</th>
</tr>
</thead>
<tbody>
<tr>
<td>Unique Analysts</td>
<td>3,246</td>
</tr>
<tr>
<td>Unique Brokerages</td>
<td>265</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Quarter End Date</th>
<th>Number of Conference Calls</th>
<th>%</th>
</tr>
</thead>
<tbody>
<tr>
<td>3/31/2002</td>
<td>49</td>
<td>1%</td>
</tr>
<tr>
<td>6/30/2002</td>
<td>304</td>
<td>4%</td>
</tr>
<tr>
<td>9/30/2002</td>
<td>404</td>
<td>5%</td>
</tr>
<tr>
<td>12/31/2002</td>
<td>555</td>
<td>7%</td>
</tr>
<tr>
<td>3/31/2003</td>
<td>606</td>
<td>7%</td>
</tr>
<tr>
<td>6/30/2003</td>
<td>735</td>
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</tr>
<tr>
<td>9/30/2003</td>
<td>740</td>
<td>9%</td>
</tr>
<tr>
<td>12/31/2003</td>
<td>865</td>
<td>10%</td>
</tr>
<tr>
<td>3/31/2004</td>
<td>815</td>
<td>10%</td>
</tr>
<tr>
<td>6/30/2004</td>
<td>846</td>
<td>10%</td>
</tr>
<tr>
<td>9/30/2004</td>
<td>877</td>
<td>10%</td>
</tr>
<tr>
<td>12/31/2004</td>
<td>879</td>
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</tr>
<tr>
<td>3/31/2005</td>
<td>841</td>
<td>10%</td>
</tr>
<tr>
<td><strong>Total</strong></td>
<td><strong>8,516</strong></td>
<td><strong>100%</strong></td>
</tr>
</tbody>
</table>
Table 1 (continued)

Panel D: Correlations\(^{c}\) (Pearson above the diagonal / Spearman below the diagonal)

<table>
<thead>
<tr>
<th>Variable</th>
<th>1</th>
<th>2</th>
<th>3</th>
<th>4</th>
<th>5</th>
<th>6</th>
<th>7</th>
<th>8</th>
<th>9</th>
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<th>12</th>
<th>13</th>
<th>14</th>
<th>15</th>
<th>16</th>
<th>17</th>
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</thead>
<tbody>
<tr>
<td>Participate</td>
<td>1.00</td>
<td>-0.02</td>
<td>0.00</td>
<td>0.02</td>
<td>0.07</td>
<td>0.01</td>
<td>-0.09</td>
<td>0.13</td>
<td>0.02</td>
<td>0.07</td>
<td>0.01</td>
<td>0.01</td>
<td>0.05</td>
<td>-0.03</td>
<td>0.12</td>
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</tr>
<tr>
<td>Delay</td>
<td>-0.06</td>
<td>1.00</td>
<td>-0.09</td>
<td>-0.13</td>
<td>0.00</td>
<td>-0.02</td>
<td>-0.07</td>
<td>-0.02</td>
<td>0.00</td>
<td>-0.02</td>
<td>0.03</td>
<td>-0.03</td>
<td>0.04</td>
<td>-0.02</td>
<td>0.01</td>
<td>0.03</td>
<td>-0.01</td>
</tr>
<tr>
<td>Horizon(^{post})</td>
<td>0.00</td>
<td>-0.09</td>
<td>1.00</td>
<td>0.81</td>
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<td>-0.21</td>
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<td>-0.07</td>
<td>-0.05</td>
<td>-0.44</td>
<td>-0.38</td>
<td>-0.05</td>
<td>0.00</td>
<td>0.01</td>
<td>-0.04</td>
<td>0.02</td>
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<tr>
<td>Horizon(^{Rpost})</td>
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<td>-0.19</td>
<td>0.80</td>
<td>1.00</td>
<td>-0.11</td>
<td>0.03</td>
<td>-0.01</td>
<td>0.05</td>
<td>-0.07</td>
<td>-0.05</td>
<td>-0.49</td>
<td>-0.41</td>
<td>-0.05</td>
<td>0.02</td>
<td>0.04</td>
<td>-0.04</td>
<td>-0.02</td>
</tr>
<tr>
<td>F_Exper(^R)</td>
<td>0.07</td>
<td>0.01</td>
<td>-0.10</td>
<td>-0.11</td>
<td>1.00</td>
<td>0.20</td>
<td>0.00</td>
<td>0.07</td>
<td>0.59</td>
<td>0.31</td>
<td>0.05</td>
<td>0.04</td>
<td>0.69</td>
<td>0.16</td>
<td>0.06</td>
<td>0.49</td>
<td>0.23</td>
</tr>
<tr>
<td>Firms(^R)</td>
<td>0.01</td>
<td>-0.03</td>
<td>0.02</td>
<td>0.03</td>
<td>0.20</td>
<td>1.00</td>
<td>0.00</td>
<td>0.18</td>
<td>0.30</td>
<td>0.18</td>
<td>-0.02</td>
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<td>0.22</td>
<td>0.14</td>
</tr>
<tr>
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<td>-0.09</td>
<td>-0.19</td>
<td>-0.01</td>
<td>0.00</td>
<td>0.00</td>
<td>1.00</td>
<td>0.00</td>
<td>0.00</td>
<td>0.01</td>
<td>0.00</td>
<td>0.00</td>
<td>0.08</td>
<td>0.12</td>
<td>0.03</td>
<td>0.02</td>
<td>0.27</td>
</tr>
<tr>
<td>Broker(^R)</td>
<td>0.13</td>
<td>-0.07</td>
<td>0.02</td>
<td>0.05</td>
<td>0.07</td>
<td>0.18</td>
<td>0.00</td>
<td>1.00</td>
<td>0.11</td>
<td>0.05</td>
<td>-0.01</td>
<td>-0.01</td>
<td>0.05</td>
<td>0.13</td>
<td>0.78</td>
<td>0.07</td>
<td>0.03</td>
</tr>
<tr>
<td>T_Exper(^R)</td>
<td>0.02</td>
<td>0.01</td>
<td>-0.07</td>
<td>-0.07</td>
<td>0.59</td>
<td>0.30</td>
<td>0.00</td>
<td>0.11</td>
<td>1.00</td>
<td>0.14</td>
<td>0.03</td>
<td>0.02</td>
<td>0.49</td>
<td>0.25</td>
<td>0.09</td>
<td>0.81</td>
<td>0.11</td>
</tr>
<tr>
<td>ForFreq(^R)</td>
<td>0.07</td>
<td>-0.02</td>
<td>-0.05</td>
<td>-0.05</td>
<td>0.31</td>
<td>0.18</td>
<td>0.01</td>
<td>0.05</td>
<td>0.14</td>
<td>1.00</td>
<td>0.04</td>
<td>0.06</td>
<td>0.13</td>
<td>0.15</td>
<td>0.03</td>
<td>0.08</td>
<td>0.68</td>
</tr>
<tr>
<td>Acc(^R)^(^{post})</td>
<td>0.01</td>
<td>0.03</td>
<td>-0.43</td>
<td>-0.49</td>
<td>0.05</td>
<td>-0.02</td>
<td>0.00</td>
<td>-0.01</td>
<td>0.03</td>
<td>0.04</td>
<td>1.00</td>
<td>0.51</td>
<td>0.02</td>
<td>-0.01</td>
<td>0.00</td>
<td>0.01</td>
<td>0.02</td>
</tr>
<tr>
<td>Acc(^R)^(^{pre})</td>
<td>0.01</td>
<td>-0.01</td>
<td>-0.37</td>
<td>-0.41</td>
<td>0.04</td>
<td>-0.01</td>
<td>-0.01</td>
<td>-0.01</td>
<td>0.02</td>
<td>0.06</td>
<td>0.51</td>
<td>1.00</td>
<td>0.01</td>
<td>0.00</td>
<td>0.00</td>
<td>0.00</td>
<td>0.03</td>
</tr>
<tr>
<td>F_Exper(^R)</td>
<td>0.06</td>
<td>0.05</td>
<td>-0.07</td>
<td>-0.07</td>
<td>0.85</td>
<td>0.18</td>
<td>0.09</td>
<td>0.06</td>
<td>0.51</td>
<td>0.27</td>
<td>0.03</td>
<td>0.02</td>
<td>1.00</td>
<td>0.18</td>
<td>0.11</td>
<td>0.63</td>
<td>0.21</td>
</tr>
<tr>
<td>Firms</td>
<td>-0.01</td>
<td>-0.02</td>
<td>-0.01</td>
<td>0.02</td>
<td>0.17</td>
<td>0.78</td>
<td>0.13</td>
<td>0.16</td>
<td>0.26</td>
<td>0.15</td>
<td>-0.01</td>
<td>0.00</td>
<td>0.23</td>
<td>1.00</td>
<td>0.13</td>
<td>0.25</td>
<td>0.27</td>
</tr>
<tr>
<td>Broker</td>
<td>0.13</td>
<td>-0.06</td>
<td>0.01</td>
<td>0.04</td>
<td>0.06</td>
<td>0.16</td>
<td>0.03</td>
<td>0.87</td>
<td>0.09</td>
<td>0.04</td>
<td>0.00</td>
<td>0.00</td>
<td>0.11</td>
<td>0.17</td>
<td>1.00</td>
<td>0.11</td>
<td>0.05</td>
</tr>
<tr>
<td>T_Exper</td>
<td>0.03</td>
<td>0.04</td>
<td>-0.04</td>
<td>-0.04</td>
<td>0.54</td>
<td>0.28</td>
<td>0.02</td>
<td>0.10</td>
<td>0.87</td>
<td>0.12</td>
<td>0.02</td>
<td>0.01</td>
<td>0.61</td>
<td>0.31</td>
<td>0.14</td>
<td>1.00</td>
<td>0.13</td>
</tr>
<tr>
<td>ForFreq</td>
<td>0.03</td>
<td>0.02</td>
<td>0.01</td>
<td>-0.02</td>
<td>0.27</td>
<td>0.14</td>
<td>0.27</td>
<td>0.04</td>
<td>0.12</td>
<td>0.73</td>
<td>0.02</td>
<td>0.04</td>
<td>0.35</td>
<td>0.27</td>
<td>0.07</td>
<td>0.17</td>
<td>1.00</td>
</tr>
</tbody>
</table>

\(^{a}\) See appendix 2 for variable definitions.

\(^{b}\) Industry definitions correspond to the 17 groups of SIC codes on Ken French’s website http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html.

\(^{c}\) Bolded correlations are significantly different from zero at p < 0.01 two-tailed level.
Table 2
OLS regression investigating the association between conference call participation and relative forecast accuracy

**Panel A: OLS pooled cross section of 57,443 analyst-firm-quarters**

\[ \text{ACC }_{R_{i,j}}^{\text{post}} = \beta_0 + \beta_1 \text{Participate}_{i,j,t} + \beta_2 \text{F}_\text{Exper }_R_{i,j,t} + \beta_3 \text{T}_\text{Exper }_R_{i,j,t} + \beta_4 \text{LnFollow}_{i,j,t} + \beta_5 \text{Firms }_R_{i,j,t} + \beta_6 \text{Broker }_R_{i,j,t} + \beta_7 \text{Horizon }_R_{i,j,t} + \beta_8 \text{ForFreq }_R_{i,j,t} + \beta_9 \text{ACC }_{R_{i,j}}^{\text{pre}} + \epsilon_{i,j,t} \]  

<table>
<thead>
<tr>
<th>Variable</th>
<th>Predicted Sign</th>
<th>Coefficient</th>
<th>Standard Error</th>
</tr>
</thead>
<tbody>
<tr>
<td>Participate</td>
<td>+</td>
<td>0.524 ***</td>
<td>0.194</td>
</tr>
<tr>
<td>F_Exper_R</td>
<td>+</td>
<td>0.001</td>
<td>0.004</td>
</tr>
<tr>
<td>T_Exper_R</td>
<td>+</td>
<td>0.000</td>
<td>0.004</td>
</tr>
<tr>
<td>Lnfollow</td>
<td>?</td>
<td>0.088</td>
<td>0.143</td>
</tr>
<tr>
<td>Firms_R</td>
<td>-</td>
<td>-0.007 *</td>
<td>0.004</td>
</tr>
<tr>
<td>Broker_R</td>
<td>+</td>
<td>0.013 ***</td>
<td>0.004</td>
</tr>
<tr>
<td>Horizon_R</td>
<td>-</td>
<td>-0.347 ***</td>
<td>0.005</td>
</tr>
<tr>
<td>ForFreq_R</td>
<td>+</td>
<td>0.002</td>
<td>0.004</td>
</tr>
<tr>
<td>Acc_R</td>
<td>+</td>
<td>0.373 ***</td>
<td>0.005</td>
</tr>
<tr>
<td>Intercept</td>
<td>?</td>
<td>48.249 ***</td>
<td>0.739</td>
</tr>
</tbody>
</table>

Sample Size 57,443
Adjusted R² 0.35

**Panel B: OLS time-series changes model with 25,010 adjacent analyst-firm-quarters**

\[ \Delta \text{ACC }_{R_{i,j}} = \alpha_0 + \alpha_1 \Delta \text{Participate}_{i,j,t} + \alpha_2 \Delta \text{Horizon }_R_{i,j,t} + \mu_{i,j,t} \]  

<table>
<thead>
<tr>
<th>Variable</th>
<th>Predicted Sign</th>
<th>Coefficient</th>
<th>Standard Error</th>
</tr>
</thead>
<tbody>
<tr>
<td>( \Delta \text{Participate} )</td>
<td>+</td>
<td>0.775 **</td>
<td>0.331</td>
</tr>
<tr>
<td>( \Delta \text{Horizon }_R )</td>
<td>-</td>
<td>-0.113 ***</td>
<td>0.010</td>
</tr>
<tr>
<td>Intercept</td>
<td>?</td>
<td>1.038 ***</td>
<td>0.176</td>
</tr>
</tbody>
</table>

Sample Size 25,010
Adjusted R² 0.01

---

\(^a\) See appendix 2 for variable definitions. \( \Delta \text{Participate} \) is defined as \( \text{Participate} \) in the current quarter minus \( \text{Participate} \) in the prior quarter for a given analyst on adjacent quarters for a given firm. \( \Delta \text{Horizon }_R \) is the relative \( \text{Horizon} \) of the first annual earnings forecast revision after the quarter \( t \) earnings announcement minus the relative \( \text{Horizon} \) of the last annual earnings forecast before the quarter \( t \) earnings announcement.

\(^b\) **, *, * Statistical significance at the 0.01, 0.05, 0.10 level, respectively, in two-tailed tests.

\(^c\) Robust standard errors are estimated using the Huber (1967)-White(1980) procedure, with analyst-level clustering for lack of independence of analyst observations over time.
Table 3
Duration from Conference Call to Forecast Revision

Panel A: Cox regressions of the timeliness of forecast revision in the pooled cross section of observations

\[
h(t) = h_0(t) \exp(\delta_0 + \delta_1 \text{Participate}_{i,j,t} + \delta_2 \text{F}_\text{Exper}_R_{i,j,t} + \delta_3 \text{T}_\text{Exper}_R_{i,j,t} + \delta_4 \text{LnFollow}_{i,j,t} + \delta_5 \text{Firms}_R_{i,j,t} + \delta_6 \text{Broker}_R_{i,j,t} + \delta_7 \text{ForFreq}_R_{i,j,t} + \delta_8 \text{Acc}_R_{i,j,t} + \mu_{i,j,t})
\]

(2a)

<table>
<thead>
<tr>
<th>Variable</th>
<th>Predicted Sign</th>
<th>Coefficient</th>
<th>Hazard Ratio</th>
<th>Standard Error</th>
</tr>
</thead>
<tbody>
<tr>
<td>Participate</td>
<td>+</td>
<td>0.052 ***</td>
<td>1.054</td>
<td>0.010</td>
</tr>
<tr>
<td>F_Exper_R</td>
<td>+</td>
<td>-0.000 **</td>
<td>1.000</td>
<td>0.000</td>
</tr>
<tr>
<td>T_Exper_R</td>
<td>+</td>
<td>-0.000</td>
<td>1.000</td>
<td>0.000</td>
</tr>
<tr>
<td>LnFollow</td>
<td>?</td>
<td>0.088 ***</td>
<td>1.092</td>
<td>0.006</td>
</tr>
<tr>
<td>Firms_R</td>
<td>-</td>
<td>0.001 ***</td>
<td>1.001</td>
<td>0.000</td>
</tr>
<tr>
<td>Broker_R</td>
<td>+</td>
<td>0.001 ***</td>
<td>1.001</td>
<td>0.000</td>
</tr>
<tr>
<td>ForFreq_R</td>
<td>+</td>
<td>0.001 ***</td>
<td>1.001</td>
<td>0.000</td>
</tr>
<tr>
<td>Acc_R^{pre}</td>
<td>+</td>
<td>0.001 ***</td>
<td>1.001</td>
<td>0.000</td>
</tr>
</tbody>
</table>

Sample size 57,443

Panel B: OLS regression of the change in timeliness of forecast revisions on changes in conference call participation in adjacent analyst-firm-quarters

\[
\Delta \text{Delay}_{i,j,t} = \gamma_0 + \gamma_1 \Delta \text{Participate}_{i,j,t} + \eta_{i,j,t}
\]

(2b)

<table>
<thead>
<tr>
<th>Variable</th>
<th>Predicted Sign</th>
<th>Coefficient</th>
<th>Standard Error</th>
</tr>
</thead>
<tbody>
<tr>
<td>\Delta \text{Participate}</td>
<td>-</td>
<td>-0.827 **</td>
<td>0.393</td>
</tr>
<tr>
<td>Intercept</td>
<td>?</td>
<td>0.683 ***</td>
<td>0.145</td>
</tr>
</tbody>
</table>

Sample Size 25,010
Adjusted R\(^2\) 0.00

\(^a\) See appendix 2 for variable definitions. \(\Delta \text{Participate}\) is defined as \(\text{Participate}\) in the current quarter minus \(\text{Participate}\) in the prior quarter for a given analyst on adjacent quarters for a given firm.

\(^b\) \(***, **, *\) Statistical significance at the 0.01, 0.05, 0.10 level, respectively, in two-tailed tests.

\(^c\) Robust standard errors are estimated using the Huber (1967)-White (1980) procedure, with analyst-level clustering for lack of independence of analyst observations over time.
Table 4
Propensity Score Analysis

Panel A: Logistic regression of the likelihood of conference call participation

\[
\text{Participate}_{i,j,t} = \beta_0 + \beta_1 \text{SBuy}_{i,j,t} + \beta_2 \text{Buy}_{i,j,t} + \beta_3 \text{Sell}_{i,j,t} + \beta_4 \text{SSell}_{i,j,t} + \beta_5 \text{QAmin}_{i,j,t} + \\
\beta_6 \text{LnFollow}_{i,j,t} + \beta_7 \text{AllStar}_{i,j,t} + \beta_8 \text{ACC}_R^{pre}_{i,j,t} + \beta_9 \text{F_Exper}_R_{i,j,t} + \\
\beta_{10} \text{T_Exper}_R_{i,j,t} + \beta_{11} \text{Inds}_R_{i,j,t} + \beta_{12} \text{ForFreq}_R_{i,j,t} + \beta_{13} \text{Broker}_R_{i,j,t} + \\
\beta_{14} \text{Firms}_R_{i,j,t} + \beta_{15} \text{CCuser}_{i,j,t} + \beta_{16} \text{PriorParticipate}_{i,j,t} + \\
\beta_{17} \text{RecHorizon}_{i,j,t} + \nu_{i,j,t}.
\]

<table>
<thead>
<tr>
<th>Variable</th>
<th>Predicted Sign</th>
<th>Coefficient $^b$</th>
<th>Standard Error $^c$</th>
</tr>
</thead>
<tbody>
<tr>
<td>SBuy</td>
<td>+</td>
<td>0.418 ***</td>
<td>0.032</td>
</tr>
<tr>
<td>Buy</td>
<td>+</td>
<td>0.396 ***</td>
<td>0.028</td>
</tr>
<tr>
<td>Sell</td>
<td>-</td>
<td>-0.183 ***</td>
<td>0.046</td>
</tr>
<tr>
<td>SSell</td>
<td>-</td>
<td>-0.325 ***</td>
<td>0.080</td>
</tr>
<tr>
<td>QAmin</td>
<td>+</td>
<td>0.016 ***</td>
<td>0.001</td>
</tr>
<tr>
<td>LnFollow</td>
<td>-</td>
<td>-0.519 ***</td>
<td>0.019</td>
</tr>
<tr>
<td>AllStar</td>
<td>+</td>
<td>0.097 *</td>
<td>0.051</td>
</tr>
<tr>
<td>ACC_R$^{pre}$</td>
<td>+</td>
<td>0.000</td>
<td>0.000</td>
</tr>
<tr>
<td>F_Exper_R</td>
<td>+</td>
<td>0.003 ***</td>
<td>0.001</td>
</tr>
<tr>
<td>T_Exper_R</td>
<td>+</td>
<td>-0.002 ***</td>
<td>0.001</td>
</tr>
<tr>
<td>Inds_R</td>
<td>-</td>
<td>-0.004 ***</td>
<td>0.001</td>
</tr>
<tr>
<td>ForFreq_R</td>
<td>+</td>
<td>0.001 *</td>
<td>0.000</td>
</tr>
<tr>
<td>Broker_R</td>
<td>+</td>
<td>0.006 ***</td>
<td>0.001</td>
</tr>
<tr>
<td>Firms_R</td>
<td>-</td>
<td>-0.005 ***</td>
<td>0.001</td>
</tr>
<tr>
<td>CCuser</td>
<td>+</td>
<td>0.206 ***</td>
<td>0.011</td>
</tr>
<tr>
<td>PriorParticipate</td>
<td>+</td>
<td>1.388 ***</td>
<td>0.036</td>
</tr>
<tr>
<td>RecHorizon</td>
<td>-</td>
<td>0.000 ***</td>
<td>0.000</td>
</tr>
<tr>
<td>Intercept</td>
<td>?</td>
<td>-0.286 ***</td>
<td>0.081</td>
</tr>
</tbody>
</table>

Sample size $^d$ 56,907
Psuedo $R^2$ 14.23%
Log Likelihood -33,760.32
Wald $\chi^2$ 3082.99
Panel B: Differences in Mean, Median and distribution of relative forecast accuracy and timeliness between participating and nonparticipating firms for the Propensity Score Matched Sample

<table>
<thead>
<tr>
<th>Variable</th>
<th>Treatment (Participating Analysts)</th>
<th>Control (Nonparticipating Analysts)</th>
<th>t-test p-value</th>
<th>Wilcoxon p-value</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Mean</td>
<td>Median</td>
<td>Mean</td>
<td>Median</td>
</tr>
<tr>
<td>Propensity Score</td>
<td>0.512</td>
<td>0.532</td>
<td>0.512</td>
<td>0.531</td>
</tr>
<tr>
<td>ACC_R^{post}</td>
<td>53.133</td>
<td>54.412</td>
<td>52.437</td>
<td>53.333</td>
</tr>
<tr>
<td>Delay</td>
<td>12.847</td>
<td>1.000</td>
<td>13.83</td>
<td>2.000</td>
</tr>
<tr>
<td>Sample size(^d)</td>
<td>13,255</td>
<td></td>
<td>13,255</td>
<td></td>
</tr>
</tbody>
</table>

\(^a\) See appendix 2 for variable definitions. Propensity Score is the predicted probability derived from the logistic regression in Panel A.

\(^b\) ***, **, * Statistical significance at the 0.01, 0.05, 0.10 level, respectively, in two-tailed tests.

\(^c\) Robust standard errors are estimated using the Huber (1967)-White(1980) procedure, with analyst-level clustering for lack of independence of analyst observations over time.

\(^d\) The sample size of 56,907 in Panel A equals the overall pooled sample of 57,433 in Table 1 less 536 analyst firm quarter observations where no outstanding recommendation was available on I/B/E/S. Of the 56,907 observations used for estimation in Panel A, 26,906 observations had the treatment effect Participate = 1. Of these 26,906 participating analysts in Panel A, matched pairs for 13,255 were identified, where matches were drawn from nonparticipating analysts without replacements and required a propensity score within 0.01 of the participating analyst.

\(^e\) Predicted signs are taken from Mayew (2008)
### Table 5
Changes in Stock Recommendations after Good or Bad News

**Panel A: Descriptive statistics for analyst recommendation samples**

**Bad News / Downgrade Sample N=13,097**

<table>
<thead>
<tr>
<th>Variable</th>
<th>Mean</th>
<th>Median</th>
<th>Std Dev</th>
<th>Minimum</th>
<th>Maximum</th>
</tr>
</thead>
<tbody>
<tr>
<td>$FE_p$</td>
<td>-0.013</td>
<td>-0.001</td>
<td>0.494</td>
<td>-55.303</td>
<td>0.000</td>
</tr>
<tr>
<td>$Rec$</td>
<td>2.384</td>
<td>3.000</td>
<td>0.903</td>
<td>1.000</td>
<td>4.000</td>
</tr>
<tr>
<td>Participate</td>
<td>0.465</td>
<td>0.000</td>
<td>0.499</td>
<td>0.000</td>
<td>1.000</td>
</tr>
</tbody>
</table>

**Good News / Upgrade Sample N = 26,915**

<table>
<thead>
<tr>
<th>Variable</th>
<th>Mean</th>
<th>Median</th>
<th>Std Dev</th>
<th>Minimum</th>
<th>Maximum</th>
</tr>
</thead>
<tbody>
<tr>
<td>$FE_p$</td>
<td>0.012</td>
<td>0.001</td>
<td>0.544</td>
<td>0.000</td>
<td>50.500</td>
</tr>
<tr>
<td>$Rec$</td>
<td>2.816</td>
<td>3.000</td>
<td>0.729</td>
<td>2.000</td>
<td>5.000</td>
</tr>
<tr>
<td>Participate</td>
<td>0.466</td>
<td>0.000</td>
<td>0.499</td>
<td>0.000</td>
<td>1.000</td>
</tr>
</tbody>
</table>
Table 5 (continued)

Panel B: Logistic regression investigating the probability of downgrading after observing bad news

\[
\Pr(\text{Downgrade}_{i,j,t+1}|FE_{i,j,t}<0) = \beta_0 + \beta_1 \text{Participate}_{i,j,t} + \beta_2 \text{SBuy}_{i,j,t} + \beta_3 \text{Buy}_{i,j,t} \\
+ \beta_4 \text{Hold}_{i,j,t} + \beta_5 \text{Sell}_{i,j,t} + \epsilon_{i,j,t}
\] (3a)

<table>
<thead>
<tr>
<th>Variable</th>
<th>Coefficient</th>
<th>Odds Ratio</th>
<th>Standard Error</th>
</tr>
</thead>
<tbody>
<tr>
<td>SBuy</td>
<td>2.937 ***</td>
<td>18.851</td>
<td>3.938</td>
</tr>
<tr>
<td>Buy</td>
<td>2.729 ***</td>
<td>15.314</td>
<td>3.185</td>
</tr>
<tr>
<td>Hold</td>
<td>1.479 ***</td>
<td>4.391</td>
<td>0.922</td>
</tr>
<tr>
<td>Participate</td>
<td>-0.145 ***</td>
<td>0.865</td>
<td>0.040</td>
</tr>
</tbody>
</table>

Sample size 13,097
Pseudo R\(^2\) 0.09
Correctly classified 77.81%

Panel C: Logistic regression investigating the probability of upgrading after observing good news

\[
\Pr(\text{Upgrade}_{i,j,t+1}|FE_{i,j,t}>0) = \alpha_0 + \alpha_1 \text{Participate}_{i,j,t} + \alpha_2 \text{Buy}_{i,j,t} + \alpha_3 \text{Hold}_{i,j,t} \\
+ \alpha_4 \text{Sell}_{i,j,t} + \alpha_5 \text{SSell}_{i,j,t} + \nu_{i,j,t}
\] (3b)

<table>
<thead>
<tr>
<th>Variable</th>
<th>Coefficient</th>
<th>Odds Ratio</th>
<th>Standard Error</th>
</tr>
</thead>
<tbody>
<tr>
<td>SSell</td>
<td>2.201 ***</td>
<td>9.036</td>
<td>0.804</td>
</tr>
<tr>
<td>Sell</td>
<td>1.861 ***</td>
<td>6.433</td>
<td>0.476</td>
</tr>
<tr>
<td>Hold</td>
<td>1.330 ***</td>
<td>3.783</td>
<td>0.226</td>
</tr>
<tr>
<td>Participate</td>
<td>0.127 ***</td>
<td>1.136</td>
<td>0.041</td>
</tr>
</tbody>
</table>

Sample Size 26,915
Pseudo R\(^2\) 0.07
Correctly Classified 79.12%

\(^a\) See appendix 2 for definitions of variables.
\(^b\) ***, **, * Statistical significance at the 0.01, 0.05, 0.10 level, respectively, in two-tailed tests.
\(^c\) Robust standard errors are estimated using the Huber (1967)-White(1980) procedure, with analyst-level clustering for lack of independence of analyst observations over time.
Table 6
Logistic Regression Investigating the Association between Conference Call Participation and Analyst Turnover

Panel A: Descriptive Statistics on Analyst Level Variables

<table>
<thead>
<tr>
<th>Variable</th>
<th>Mean</th>
<th>Median</th>
<th>Std Dev</th>
<th>Min</th>
<th>Max</th>
</tr>
</thead>
<tbody>
<tr>
<td>A_Participate</td>
<td>0.614</td>
<td>0.750</td>
<td>0.400</td>
<td>0.000</td>
<td>1.000</td>
</tr>
<tr>
<td>A_Turnover</td>
<td>0.018</td>
<td>0.000</td>
<td>0.134</td>
<td>0.000</td>
<td>1.000</td>
</tr>
<tr>
<td>A_ACC_R</td>
<td>58.093</td>
<td>60.086</td>
<td>20.014</td>
<td>0.000</td>
<td>100.000</td>
</tr>
<tr>
<td>A_Delay</td>
<td>14.110</td>
<td>6.600</td>
<td>17.676</td>
<td>1.000</td>
<td>91.000</td>
</tr>
<tr>
<td>A_Total_Exper</td>
<td>5.264</td>
<td>4.000</td>
<td>5.375</td>
<td>0.000</td>
<td>22.000</td>
</tr>
<tr>
<td>A_ForFreq</td>
<td>4.321</td>
<td>4.000</td>
<td>2.157</td>
<td>0.000</td>
<td>22.429</td>
</tr>
</tbody>
</table>

Panel B: Logistic Regression (dependent variable is analyst turnover)

<table>
<thead>
<tr>
<th>Variable</th>
<th>Prediction</th>
<th>Coefficient</th>
<th>Odds Ratio</th>
<th>Standard Error</th>
</tr>
</thead>
<tbody>
<tr>
<td>A_Participate</td>
<td>-</td>
<td>-0.377*</td>
<td>0.686</td>
<td>0.138</td>
</tr>
<tr>
<td>A_ACC_R</td>
<td>-</td>
<td>0.005</td>
<td>1.005</td>
<td>0.004</td>
</tr>
<tr>
<td>ln(A_Delay)</td>
<td>+</td>
<td>-0.141**</td>
<td>0.869</td>
<td>0.057</td>
</tr>
<tr>
<td>ln(A_Total_Exper)</td>
<td>-</td>
<td>-0.181*</td>
<td>0.835</td>
<td>0.078</td>
</tr>
<tr>
<td>ln(A_ForFreq)</td>
<td>-</td>
<td>0.072</td>
<td>1.075</td>
<td>0.160</td>
</tr>
</tbody>
</table>

Sample size 7,189
Pseudo $R^2$ 0.01
Correctly classified 98.16%

*a See appendix 2 for variable definitions. Natural logarithm transformations of variables with values equal to zero are set to zero.
*b ***, **, * Statistical significance at the 0.01, 0.05, 0.10 level, respectively, in two-tailed tests.
*c Robust standard errors are estimated using the Huber (1967)-White(1980) procedure, with analyst-level clustering for lack of independence of analyst observations over time.