Using Earnings Conference Calls to Identify Analysts with Superior Private Information

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Using Earnings Conference Calls to Identify Analysts with Superior Private Information

Abstract

We examine the extent to which analysts who *participate* in earnings conference calls by asking questions possess superior private information relative to analysts who do not ask questions. Using a large sample of earnings conference call transcripts over the period 2002 to 2005, we find that annual earnings forecasts issued immediately subsequent to a conference call are both more accurate and timelier for participating analysts relative to nonparticipating analysts. These results hold after controlling for observable analyst characteristics, suggesting conference call participation can serve as a mechanism to identify analysts possessing superior private information. The economic magnitude of the superior private information contained in participating analyst forecasts is small but comparable with magnitudes reported in prior studies with respect to other analyst characteristics. Our mediation analysis does not support the notion that the superior private information stems exclusively from the information received during the call. Therefore, from a regulatory stand point, our results suggest that regulatory intervention to allow for equal participation during conference calls may be unwarranted.

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

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

1. Introduction

The purpose of this paper is to investigate whether individual analysts who *participate* in a public earnings conference call by asking questions possess superior private information relative to analysts who do not participate. Our investigation is motivated by both the basic need of investors to identify analysts with superior information in order to facilitate more informed resource allocation decisions and by regulators interested in maintaining a level informational playing field among analysts. Subsequent to the passage of Regulation FD, market participants can observe which analysts obtain "access to management" by observing which analysts ask questions during an earnings conference call. However, whether conference call participation *per se* indicates analysts' superior private information is ultimately an empirical matter because theory offers competing predictions.

Kim and Verrecchia (1997) suggest public information can play a complementary role to an individual's private information set. If analysts possessing superior private information reap information complementarities by participating on a conference call, conference call participation would serve as a means to identify those analysts possessing superior private information. On the other hand, Libby et al. (2008) challenge the assertion that participating analysts obtain any informational *private* benefit from a public dialog with management. This view is grounded in the theoretical notion that public information can substitute for private information (Verrecchia 1982; Diamond 1985). If analysts who possess superior private information view substitution effects as dominant, they may instead explicitly avoid conference call participation (i.e., avoid asking questions) so as to prevent their superior private information from becoming a public good. In such a case, lack of conference call participation would serve to identify analysts with superior private information.

Our analysis is based on over 56,000 analyst-firm-quarter post-Regulation FD observations between 2002 and 2005. We use conference call transcripts to identify which analysts from the I/B/E/S population participated in firms' quarterly earnings conference calls.[1] We then classify analysts as

[1] Conference call transcripts are not available prior to 2002, which inhibits an investigation of conference call access before and after Regulation FD. Subsequent to 2005, we are no longer able to obtain I/B/E/S translation tables that

participating (nonparticipating) if they ask (do not ask) a question during the conference call and investigate whether participating analysts appear to possess superior private information relative to nonparticipating analysts.

The possession of superior private information by an individual analyst is inherently unobservable.[2] We proxy for the presence of superior private information via the accuracy and timeliness of the initial annual earnings forecast issued immediately after a conference call under the assumption that analysts possessing superior private information will issue forecasts that are both more accurate and timely. We use both a propensity score matching and a changes (i.e., differences) research design to investigate the association between participation and forecast accuracy as well as between participation and timeliness. The propensity matching ensures that we remove the confounding effects of stable analyst quality characteristics like effort and ability because higher quality analysts are both more likely to participate on a conference call (Mayew 2008) and provide higher quality forecasts (Clement 1999).

After controlling for observable analyst quality characteristics, we find that the relative accuracy of participating analysts' initial forecasts of upcoming annual earnings 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 conference call participation can assist in identifying those analysts possessing superior private information. The results are also consistent with analysts viewing the public dialog on a conference call as complementing their private information rather than as a substitute (Mayo 2006; Erdos and Morgan 2008; Mayo 2010).

While analysts may perceive potential complementarities, it is unclear to what extent the superior accuracy and timeliness demonstrated by participating analysts result specifically from information obtained during the actual question and answer dialog of the conference call. At one extreme, the

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identify the names of the analysts in I/B/E/S, which is necessary to match observations in I/B/E/S with analysts listed in the conference call transcripts.

[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 private information measurement at the individual analyst level, nor whether such private information is differentially superior. As such, we are unable to use this measure in our empirical tests.

conference call dialog may complement an analyst's otherwise useless piece of private information in a way that makes it useful. In such a case, all of the relative superiority in accuracy and timeliness would stem from the conference call discussion *per se*, rendering conference call access a particularly lucrative commodity in the analyst community. At the other extreme, the conference call dialog may do very little to enhance a piece of superior private information that the analyst already possessed prior to the conference call. In such a case, conference call participation *per se* enhances private information very little, and instead simply provides a signal of analysts with superior private information independent of the conference call. Understanding the extent to which actual conference call participation *per se* facilitates the production of superior private information is important for regulators commissioned with maintaining a level information playing field among analysts (Cox 2005; Morgenson 2005).

To investigate this issue, we conduct a mediation analysis. If conference call access *per se* facilitates superior private information production, managers retain a discrimination tool whereby only those analysts who "curry favor" with management reap the participation rewards. This implies that conference call participation is the path through which actions to "curry favor" influence the generation of superior private information. To empirically test this implication, we examine how the association between analyst actions to curry favor with management and accuracy and timeliness changes in the presence of conference call participation. To proxy for the extent to which analysts curry favor with management, we use analysts stock recommendations (Mayew 2008; Westphal and Clement 2008; Cohen et al., 2008). Consistent with prior work (Chen and Matsumoto 2006), we find that recommendation downgrades are associated with decreases in relative accuracy. However, we do not observe a statistically significant mediating effect of conference call participation on the association between recommendation downgrades and forecast accuracy. We also observe no mediation effects for forecast timeliness. Rather, both recommendation changes and conference call participation changes incrementally predict both accuracy and timeliness changes. Collectively, these results suggest that currying favor with management cannot fully explain the observed forecasting superiority of participating analysts. Coupled with the arguably small economic magnitude of the overall results—which reveal that participating analysts are about 1% more accurate and 1 day faster than nonparticipating analysts—we conclude that regulatory intervention over analyst conference call participation for the purpose of leveling the information playing field may be unnecessary.

This paper makes the following contributions. First, we characterize a new benefit of public conference calls for investors. Prior research has established that conference calls have information content overall (Frankel et al. 1999) and that important information can be gleaned from the question and answer portion of the conference call (Matsumoto et al. 2011, Hollander et al. 2010; Mayew and Venkatachalam 2012). Our results suggest that by examining which analysts participate during an earnings conference call, investors can identify analysts who possess relatively superior private information.

Second, we offer new insights on the accuracy and timeliness tradeoff analysts face when forecasting earnings (Schipper 1991). 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). We find that participating analysts are *both* more timely and more accurate in their forecasts, suggesting accuracy is not always sacrificed at the expense of timeliness.

Third, we add to the literatures on i) the complementarities versus substitution effects of public information disclosures and ii) the benefits of access to management in the post FD era. That participating analysts are relatively more accurate and timely is at a minimum consistent with analysts not fearing substitution effects as a dominant force. However, we are unable to quantify significant information complementarities arising from the conference call dialog *per se*. This is potentially suggestive that some of the expected benefits analysts perceive from participation include non-information benefits such as reputation enhancement (Libby et al. 2008). We view an empirical analysis investigating non-informational benefits accruing to participating analysts as an important issue for future research to increase our understanding of reciprocal exchanges that occur between analysts and managers in the post-FD environment (Westphal and Clement 2008; Cohen et al. 2010).

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. Related Literature and Hypothesis Development

Investors naturally seek to understand which analysts' opinions they should weigh more or less as it affects their welfare. Ramnath et al. (2008) review the literature on the factors that make analyst outputs useful to investors, many of which include characteristics of analysts themselves. The general conclusion from this literature is that analysts with more experience, more resources, more past forecasting success, those holding less complex coverage portfolios, and those who put forth more effort generate superior outputs like earnings forecasts. However, Ramnath et al. (2008) notes that "much still remains to be explained" in terms of characterizing superior analysts.

We put forward conference call participation as a potential analyst characteristic that can assist in the identification of analysts who possess superior information about a firm. With the passage of Regulation FD in 2000, conference call dialogs between managers and analysts have become increasingly public (Skinner 2003). Research has shown that conference calls overall (Frankel et al., 1999; Bushee et al. 2004), and particularly the question and answer portion of the call (Hollander et al. 2010; Matsumoto et al. 2011; Mayew and Venkatachalam 2012), provide useful information to capital market participants. More important, for our purposes, public conference calls also allow for the identification of those analysts who, among the set of analysts following a firm, *participated* in the conference call by asking a question.

Making sharp *ex ante* predictions about whether one should expect participation or nonparticipation to indicate analyst possession of superior private information is difficult because theory offers competing views. Analysts should rationally seek conference call participation whenever the benefits outweigh the costs of doing so. If the theory that public information can complement private information (Kim and Verrecchia 1997; Barron et al. 2002) is sufficiently descriptive, analysts should view a public conference call dialog as beneficial in expectation because it can enhance existing private information.[3] This implies that participation in a call is an indicator of analysts with superior information. Analyst outcry for equal conference call participation is consistent with analysts perceiving some informational benefit from the public discussion (Mayo 2002; Davis 2004; Jones 2005; Morgenson 2005; SIA 2005; Lowengard 2006; Mayo 2006; Mayo 2010).[4]

On the other hand, Libby et al. (2008) challenge the assertion that participating analysts should expect any informational benefit from a public exchange with management, stating "Given that answers to conference call questions are now immediately made public, the exact nature of the benefits from conference call participation is not clear (p. 194)." This view is grounded in the theoretical notion that public information can substitute for private information (Verrecchia 1982; Diamond 1985). If analysts expect substitution effects to dominate, participation at best would provide no incremental enhancement to existing private information. At worst, participation could be costly if an analyst's superior private information gets revealed to other competing analysts through the public dialog. Under this scenario, the lack of participation signals superior private information.

Given the differential predictions for conference call participation, which perspective dominates is ultimately an empirical issue. To test for these competing predictions, we require a proxy for superior private information. We use forecast accuracy and timeliness as our measures of superior private information because 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). Specifically, we use the timeliness and accuracy of the initial annual earnings forecast issued immediately after a conference call. While prior research guides our use of accuracy (Chen and Matsumoto 2006; Mohanram and Sunder 2006) and timeliness (Schipper 1991; Clement and Tse 2003), we acknowledge that institutional investors may not

[3] This assumes analysts ask questions conditional on their existing private information and that all analysts do not possesses the same private information. In such a case, the public answer to these questions will uniquely complement the information set of the asking analyst but at the same time do not inform competing analysts who are listening in on the same call.
[4] In testimony to the U.S. Senate Committee on Banking, Housing and Urban Affairs, Mike Mayo, a leading analyst on Wall Street, suggested that being denied conference call access by management could informationally "handicap" an analyst (Mayo 2002).

necessarily value aggregate analyst outputs like earnings forecasts *per se* as highly as individual insights about a firm's value drivers (Johnson 2005; Bagnoli et al. 2008; Groysberg et al. 2008).[5] As such, our proxies for superior private information based on properties of the initial annual earnings forecasts provided immediately subsequent to the conference call are based on the assumption that these earnings forecasts properties are correlated with the superior informational insights that analyst investor clients find valuable.

3. 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.[6] The analyst following associated with this resulting set of 26,662 firm quarter observations represent our proxy for the

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[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.

[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.

population of analysts who could potentially participate in the firm's quarterly earnings conference call.[7] From each conference call transcript, we proceed 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 an analyst as participating (nonparticipating) if they asked (did not ask) a question during 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. This restriction is imposed because we are interested in within-firm variation among analysts following the same firm rather than comparing analysts across firms. Finally, requiring a measure of analyst forecast frequency over the preceding calendar year and an outstanding stock recommendation reduces our final sample to 56,907 analyst firm quarter observations spanning the years 2002 through 2005, representing 8,516 firm quarter conference calls of 1,919 unique firms with 3,218 unique analysts from 262 unique

[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 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.

brokerages. Table 1 provides variable definitions, and Table 2 presents descriptive statistics for the main variables in our models for these 56,907 analyst firm quarter observations.

3.2. Research Design

Analyst conference call participation is not random, and it results from both an analyst actively seeking access and from management granting access by allowing a question to be asked.[8] Existing research by Mayew (2008) models the determinants of analyst participation as a function of observable analyst characteristics. Results in Mayew (2008) show analysts of higher quality and those with more favorable outstanding stock recommendations are more likely to participate on a conference call. It is critical to remove the effects of observable analyst characteristics because we are interested in examining the ability of conference call participation to identify superior private information beyond existing identifiable analyst traits documented in the literature. If, for example, analysts with higher prior forecast accuracy are more likely to select into conference call participation (Mayew 2008) and have more accurate future earnings forecasts (Brown 2001), observing a positive association between conference call participation and more accurate annual earnings forecasts subsequent to a conference call would not be surprising.

To remove the confounding selection effects pertaining to established analyst characteristics, we use a propensity score matching procedure (Rosenbaum and Rubin 1983). In particular, for the set of participating analysts, we identify a matched set of analysts who did not actually participate but who should have participated (i.e., would have fallen under the treatment group) given observable characteristics. We use a simple nearest-match method, which involves two steps. In step one, we estimate a logistic regression of participation to construct a propensity score for each analyst-firm-quarter observation, which is the conditional probability of receiving the treatment effect (i.e., the probability that an analyst participates) given a set of observable characteristics that determine participation. In step two, for each of the participating analysts we identify a nonparticipating analyst with the closest match, without replacement, in terms of the propensity score.

[8] It is not empirically possible to identify the set of analysts who sought participation, but were not chosen by management to participate, because the question queue is unobservable.

To execute step one, we follow Mayew (2008) and estimate the following pooled logistic regression using the full sample of 56,907 analyst firm quarter observations to determine the conditional probability of an analyst's quarterly earnings conference call participation:

$$\begin{aligned} Participate_{i,j,t} = \beta_0 &+ \beta_1 SBuy_{i,j,t} + \beta_2 Buy_{i,j,t} + \beta_3 Sell_{i,j,t} + \beta_4 SSell_{i,j,t} + \beta_5 QAmin_{i,j,t} \\ &+ \beta_6 LnFollow_{j,t} + \beta_7 AllStar_{i,j,t} + \beta_8 ACC\_R^{pre}{}_{i,j,t} + \beta_9 F\_Exper\_R_{i,j,t} \\ &+ \beta_{10} T\_Exper\_R_{i,j,t} + \beta_{11} Inds\_R_{i,j,t} + \beta_{12} ForFreq\_R_{i,j,t} + \beta_{13} Broker\_R_{i,j,t} \\ &+ \beta_{14} Firms\_R_{i,j,t} + \beta_{15} CCuser_{i,j,t} + \beta_{16} PriorParticipate_{i,j,t} \\ &+ \beta_{17} RecHorizon_{i,j,t} + \upsilon_{i,j,t}\,. \end{aligned} \tag{1}$$

The dependent variable, *Participate,* is an indicator variable that represents whether the analyst asked a question during the conference call. To capture how favorably the analyst views the firm, we include indicator variables (*SBuy, Buy, Sell,* and *SSell*) for the analyst's most recent outstanding stock recommendation prior to the conference call. To capture time and competition constraints we include the length of the question and answer session (*QAmin)* and the extent of analyst following (*LnFollow*). Regarding observable analyst characteristics, we include relative prior forecast accuracy (ACC_R^{pre}), relative firm (*F_Exper_R*) and total (*T_Exper_R*) experience, relative effort in forecasting (*ForFreq_R*) and interest in the firm (*RecHorizon*), relative resources (*Broker_R*) and portfolio complexity in terms of firms (*Firms_R*) and industries (*Inds_R*) followed. We also include whether the analyst was identified as an Institution Investor Research All-American (*AllStar*), the extent to which the analyst participates in other firms' conference calls (*CCuser*), and participation in the past conference calls of the firm for which the analyst currently attends (*PriorParticipate*). More detailed definitions of each of the variables in equation (1) are in Table 1.

Estimation results are provided in Panel A of Table 3. All coefficients 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 R^2 is 14.2%, which is of comparable magnitude to the 20% documented in Mayew (2008). Collectively, the behavior of the independent variables and the 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.

We then create a matched control sample based on propensity scores. That is, for each observation where *Participate* equals one, we search for an observation without replacement where *Participate* equals zero, but where the difference in propensity scores between the treatment-control pair is not different by more than 0.01.[9] Using this procedure, we are able to identify 13,255 analyst firm quarter pairs. Table 3 Panel B reveals the mean and median propensity score does not statistically differ (p = 0.970) between analyst firm quarter observations where *Participate* equals one (i.e., the treatment group) and *Participate* = 0 (i.e., the control group).

4. Results

4.1. Propensity Score Matched Differences in Accuracy and Timeliness

To examine whether participating analysts differ with respect to accuracy and timeliness compared with nonparticipating analysts, we test for mean and median differences in forecast accuracy and timeliness using the matched treatment and control groups. We measure forecast accuracy (ACC_R^{post}) as the relative accuracy of the analyst's first forecast of annual earnings following the day of the earnings announcement and conference call. For ease of interpretation, ACC_R^{post} is ranked and bounded between 0 and 100 following Ke and Yu (2006), where higher scores indicate more accurate forecasts. Our relative accuracy measure is measured at the full sample level, yielding mean values that differ from the theoretical value of 50 when subsamples of the data are utilized in the propensity score analysis. We measure forecast timeliness (*Delay*) as the number of days elapsed from the earnings announcement and conference call date until the first forecast of annual earnings. See Figure 1 for a visual depiction and details underpinning the construction of these accuracy and timeliness measures.

Panel B of Table 3 reveals that participating analysts are both more accurate and timely than nonparticipating analysts. Participating analysts are statistically more accurate forecasters than nonparticipating analysts by 0.696 units (p = 0.050) at the mean and 1.079 units (p = 0.060) at the

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[9]Relaxing the restriction of the difference in propensity score from .01 to .05 does not impact our inferences.

median. Since relative accuracy ranges from 0 to 100, these magnitudes roughly equate to differences of 0.696% and 1.079%. Although a reader might view these differences as economically small, these effects are of a similar order of magnitude to the analyst characteristics examined in Ke and Yu (2006), who note differences of 1.30 (0.60) units between an analyst with the relatively least and most amount firm experience (number of firms covered).[10]

With respect to timeliness, participating analysts deliver forecasts statistically faster by 0.983 days ($p < 0.01$) at the mean and 1 day ($p < 0.01$) at the median. Comparing these participation effects on timeliness with other analyst characteristics is difficult because we do not know of any papers that have modeled the determinants of the time until an analyst issues a forecast after a conference call. However, in absolute economic terms, the roughly 24 hour difference may be material to analysts. When discussing the effects of not being able to participate on a conference call due to willful intervention of management, Lowengard (2006) states: "for an analyst looking to put out a fast note, four hours may as well be 400." Further, 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 quarterly earnings as quickly as possible after the earnings conference call with the objective of being the first to notify clients, relative to other analysts.

4.2. Robustness Checks

To ensure the inferences from our propensity score matching research design are robust, we conduct numerous robustness checks as follows.

4.2.1. Covariate Imbalance

In untabulated results, we test whether the means (medians) of the independent variables in equation (1) 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

[10] These values are obtained from Table 3, Column 1 of Ke and Yu (2006). The two analyst specific characteristics examined are relative firm experience and relative number of firms covered, which have statistically significant marginal effects of 0.013 and -0.006, respectively. These point estimates are multiplied by 100 to estimate differences in relative annual forecast accuracy, because relative firm experience and relative number of firms covered are ranked and bounded between 0 and 100.

that our matching scheme was reasonably successful in ensuring covariate balance. To ensure the lack of covariate balance does not influence our inferences, we estimate the following OLS models for the 26,510 observations that make up the propensity score matched sample with standard errors clustered by analyst:

$$ACC\_R^{post}_{i,j,t} = \beta_0 + \beta_1 Participate_{i,j,t} + \beta_2 LnFollow_{i,j,t} + \beta_3 Firms\_R_{i,j,t} + \varepsilon_{i,j,t} \qquad (2a)$$

$$Delay_{i,j,t} = \alpha_0 + \alpha_1 Participate_{i,j,t} + \alpha_2 LnFollow_{i,j,t} + \alpha_3 Firms\_R_{i,j,t} + \varpi_{i,j,t} \qquad (2b)$$

Untabulated results reveal a coefficient on β_1 (α_1) of 0.700, p = 0.047 (-0.897, p = 0.007), which are very similar to the mean differences noted in Table 3 Panel B. We conclude that the lack of covariate balance does not affect our inferences.[11]

4.2.2. Interaction of Accuracy and Timeliness

The analysis thus far provides evidence separately for accuracy and timeliness of analyst forecast with both pointing towards conference call participation as an indicator of superior private information. In this section we consider differences in forecast accuracy of participating and nonparticipating analysts conditional on the timing of their forecasts. More specifically, the superior accuracy of participating analysts should be particularly salient whenever nonparticipating analysts issue a forecast before participating analysts. On the other hand, nonparticipating analysts who wait and issue their forecasts after participating analysts should be able to utilize the participating analyst forecasts and other public information to improve their accuracy, in turn eroding the superior accuracy that participating analysts seem to enjoy.

To test this prediction, we partition the treatment and control samples from the propensity score analysis based on the median sample forecast timeliness. In particular, we isolate those observations where *Delay* <= 1 and where *Delay* > 1 in both the treatment and control groups, and calculate the average relative forecast accuracy (ACC_R^{post}) for each of the resulting four cells. The results are

[11] Since *Delay* is not a relative measure, it is possible that firm characteristics not considered in equation (1) impact participation and timeliness. To address this issue, we re-estimate equation (2b) but include the sign and magnitude of unexpected earnings, quarter of year fixed effects, and year fixed effects. The coefficient on *Participate* remains negative and significant (β_1 =-0.657, p = 0.047). Further, since *Delay* is a count variable, OLS may not be the appropriate estimation technique, particularly if extreme values in *Delay* influence our inferences. If we re-estimate this augmented version of (2b) using logistic regression, and replace *Delay* with an indicator that equals 1 if *Delay* >=2 and zero otherwise, we continue to observe a negative and statistically significant coefficient on *Participate* (-0.243, p <= 0.01). Inferences are also unchanged if we use relative delay as the dependent variable.

provided in Table 3, Panel C. We find that nonparticipating analysts issuing forecasts earlier than participating analysts are less accurate (51.771 vs. 53.953), and the difference is statistically significant (p <= 0.001). This is consistent with nonparticipating analysts holding less superior private information relative to participating analysts. However, nonparticipating analysts who wait until after participating analysts have forecasted are slightly more accurate (53.073 vs. 52.470) although the difference is not statistically significant (p = 0.226).[12] This is consistent with nonparticipating analysts utilizing publicly available information, potentially from participating analysts, to improve their forecast accuracy to the level of the participating analyst.

4.2.3. Changes Analysis

The propensity score matching procedure assumes that factors excluded from model (1) are not confounding factors. It is possible, however, that other unmeasured factors drive participation, timeliness and accuracy. Additionally, propensity score analysis requires finding matches for each treatment observation, and as a result is comprised of only a subset of the data that may not generalize to the population. To help ensure our inferences are not confounded by the propensity score match design, we return to the full sample to examine changes in forecast accuracy and timeliness for the same analyst following the same firm during consecutive quarters.

Specifically, we estimate the following pooled cross-sectional OLS model with standard errors clustered by both analyst and the calendar quarter in which the conference call was held, for changes in relative accuracy and timeliness, respectively:

$$ddACC\_R_{i,j,t} = \delta_0 + \delta_1 \Delta Participate_{i,j,t} + CONTROLS + \mu_{i,j,t} \quad (3a)$$
$$\Delta Delay_{i,j,t} = \gamma_0 + \gamma_1 \Delta Participate_{i,j,t} + CONTROLS + \eta_{i,j,t} \quad (3b)$$

In model (3a), the dependent variable $ddACC\_R_{i,j,t}$ is the difference in relative accuracy changes, measured as $\Delta ACC\_R_{i,j,t}$ - $\Delta ACC\_R_{i,j,t-1}$, where $\Delta ACC\_R_{i,j,t} = ACC\_R^{post}_{i,j,t} - ACC\_R^{pre}_{i,j,t}$. That is, we compare the change in relative accuracy surrounding the quarter t conference call for analyst i following

[12] Decomposing the treatment and control groups by timeliness does not preserve propensity score balance across the cells we compare statistically. If we remove observations until we achieve insignificant differences at the 10% significance level in propensity scores and redo the analysis, our inferences are unchanged.

firm j with the change in relative accuracy surrounding the quarter $t-1$ conference call. In model (3b) the dependent variable $\Delta Delay_{i,j,t}$ is the change in the number of days elapsed between the conference call and the first earnings forecast, measured as $Delay_{i,j,t} - Delay_{i,j,t-1}$. In both equations, the independent variable is the change in quarter over quarter conference call participation, $\Delta Participate_{i,j,t}$ measured as $Participate_{i,j,t} - Participate_{i,j,t-1}$. In the changes specification, any stable observable or unobservable analyst, firm, or analyst-firm specific factors are differenced away. *CONTROLS* represent explicit measurement of quarter over quarter changes in a vector of observable analyst and forecast based characteristics discussed below that are constructed from the full sample of observations at each earnings conference call date.

Conceptually, it is important to control for analyst effort, since effort changes could yield changes in both participation and in forecast accuracy or timeliness. Unfortunately, effort is unobservable, so we attempt to control for effort following extant literature (Clement and Tse 2003; Clement and Tse 2005). First, we include changes in primitive factors that influence an analyst's cost of effort: relative overall and firm-specific experience (*T_Exper_R* and *F_Exper_R*), relative resources as proxied by relative broker size (*Broker_R*), and relative portfolio size (*Firms_R*), because as portfolio size increases analyst effort must be distributed across a larger number of firms. Second, we include changes in observable forecasting effort measured as the relative forecasting frequency of the analyst during the year prior to the quarter t earnings announcement (*ForFreq_R*).

All of the above analyst characteristic variables are computed in relative form as follows:

$Characteristic\_R = 100 - \frac{Characteristic\_revrank_{i,j,t} - 1}{Follow_{j,t} - 1} x100$, where *Characteristic* = *T_Exper, F_Exper, Broker*, *Firms,* ACC^{pre}, and *ForFreq*. *Characteristic_revrank* is the reverse ranking of each characteristic yielding higher ranks for higher values on each characteristic. *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. We also control for changes in analyst competition, as proxied by the level of analyst following (*LnFollow*).

Finally, forecasts with shorter horizons are closer to the actual realization of earnings and as such have the advantage of incorporating more information about upcoming annual earnings than forecasts issued at longer horizons. To accommodate the natural inverse relation between accuracy and timeliness, in equation (3a) and (3b) we also include changes in the relative distance from the earnings forecast issued immediately after the conference call ($Horizon\_R^{post}$) and changes in the relative accuracy of the analyst's last annual forecast issued immediately before the earnings announcement (ACC_R^{pre}), respectively. We do not include changes in $Horizon\_R^{post}$ [ACC_R^{pre}] in equation (3b) [(3a)] however, because $Horizon\_R^{post}$ [ACC_R^{pre}] is mechanically related to the dependent variable *Delay* [*ddACC_R*] (see Figure 1).

We identify 24,073 analyst firm quarter observations from the original sample with requisite data to measure quarter over quarter changes in each of the variables included in equation (3a) and (3b). Descriptive statistics for the variables are presented in Table 4, Panel A. The average change in participation is close to zero. We find 70% of observations exhibit no change in participation status, consistent with the potent explanatory power of prior participation in the participation determinant model in Table 3, Panel A and Mayew (2008). Participation changes are roughly symmetric, where 15.3% (14.7%) of observations move from nonparticipation (participation) in the immediate prior quarter to participation (nonparticipation) in the current quarter.

Regarding the association between participation changes and accuracy changes, we find in Column A of Table 4, Panel B that changes in conference call participation are positively associated with changes in relative forecast accuracy ($\delta_1 = 1.225$, p = 0.017), before including control variables. After including control variables in Column B, the results are nearly identical ($\delta_1 = 1.205$, p = 0.019). These results suggest the improvement (deterioration) in relative forecast accuracy for forecasts straddling a conference call is greater (smaller) for analysts who participated (did not participate) in the current quarter but did not participate (participated) in the previous quarter. This is consistent with conference call access identifying analysts possessing superior private information, and is of similar magnitude to the median participation effects in the propensity score analysis of 1.079 in Table 3, Panel B.

Regarding the effects of participation changes on timeliness, we find in Column C of Table 4, Panel B that changes in participation reduces the delay in forecast issuance (γ_1 = -0.847, p = 0.019). This implies that analysts who participated (did not participate) delivered their forecasts to the market 0.847 days faster (slower) compared to their delivery in the prior quarter when they did not participate (did participate). After controlling for other factors, the coefficient is largely unchanged (γ_1 = -0.788, p = 0.028). These participation effects are similar in magnitude to the average difference of -0.983 observed in the propensity score matched analysis, suggesting our inferences are robust.

5. Implications

5.1 Source of Superior Private Information for Participating Analysts

As a collection, the results in section 4 are consistent with conference call participation serving as an indicator of analysts' superior private information. However, an unresolved issue is whether the superior private information of participating analysts is acquired primarily before the conference call, or acquired based on the responses to questions during the conference call. Understanding the extent to which this information superiority stems from the actual conference call discussion is important to regulators charged with maintaining a level information playing field among analysts (Cox 2005; Morgenson 2005). Some analysts contend that conference call access *per se* facilitates superior information production, and as a result if management prevents access to a particular analyst, it places the denied analyst at an informational disadvantage (Mayo 2002; SIA 2005; Lowengard 2006).

To examine this issue, it would be ideal to measure the extent of superior private information for a participating analyst at short intervals preceding and during the conference call. However, we cannot observe the private information of an individual analyst over the short intervals preceding and during a conference call. Instead, we focus on the extent to which an analyst has "curried favor" with management. If managers know that an analyst's superior private information comes from the conference call *per se*, they can effectively "charge for access" by demanding analysts to curry favor by issuing favorable stock recommendations (Chen and Matsumoto 2006; Mayew 2008; Westphal and Clement 2008; Cohen et al. 2010).[13] In such a case, currying favor should lead to conference call access, which in turn should lead to more superior private information. Put differently, currying favor should result in superior private information through the act of participation, implying conference call access is a mediating factor.[14]

To execute our mediation analysis, we extend our changes analysis from section 4.2.3 to incorporate recommendation changes as follows:

$$ddACC\_R_{i,j,t} = \delta_0 + \delta_1\, \Delta Participate_{i,j,t} + \delta_2\, Downgrade_{i,j,t} + CONTROLS + \mu_{i,j,t} \tag{3c}$$

$$\Delta Delay_{i,j,t} = \gamma_0 + \gamma_1\, \Delta Participate_{i,j,t} + \gamma_2\, Downgrade_{i,j,t} + CONTROLS + \eta_{i,j,t} \tag{3d}$$

where *Downgrade* captures downward recommendation changes and equals one if the analyst downgraded the firm since the prior conference call and zero otherwise. We focus on recommendation changes because of three separate associations documented in the literature which hold in our sample: recommendation changes are associated with changes in relative forecast accuracy (Chen and Matsumoto 2006), recommendation changes are associated with conference call participation changes (Mayew 2008), and conference call participation changes are associated with changes in relative forecast accuracy as shown in Table 4, Panel B. This collective evidence is potentially consistent with conference call participation behaving as a mediator, but by no means conclusive.

To test for mediation effects, we estimate equation (3c) stepwise by first examining the effects of downward recommendations in isolation. In Column A of Table 4, Panel C, we observe that downgrading analysts experience a decline in their forecast accuracy (coefficient = -1.852, p-value = 0.046). This result is consistent with Chen and Matsumoto (2006) and a necessary condition for proceeding with a mediation analysis. If changes in conference call access represent the path through

[13] An alternative proxy to curry favor is using the optimistic/pessimistic (OP) pattern in annual forecasts (Richardson et al. 2004; Ke and Yu 2006; Libby et al. 2008). However, since we analyze quarterly earnings conference calls, whether a given annual earnings forecast updated after a conference call will ultimately fall into the OP category is unclear until annual earnings are reported. As a result, a manager may not know whether the annual forecasts we analyze are "pleasing" at the time they are provided to the market. Recommendation changes occurring between consecutive conference calls, however, are signals observable to management before they make decisions about conference call access and can be relatively unambiguously identified as currying favor or not.

[14] We thank an anonymous referee for suggesting this mediation analysis.

which changes in recommendations influence relative forecast accuracy, when both *Downgrade* and *ΔParticipate* are included in the same regression, the effects attributable to recommendation changes should begin to disappear. On the other hand, if manager-granted conference call access is the sole driver of the association between downgrades and relative forecast accuracy changes, the coefficient on *Downgrade* will not be different from zero (i.e., perfectly mediating).

Results from including both recommendation changes and participation changes in the same specification are provided in Column B of Table 4, Panel C. The coefficient on *ΔParticipate* remains positive and statistically significant at levels very similar to Column B of Table 4, Panel B. The coefficient on *Downgrade* also remains significantly negative at levels slightly closer to zero than compared with Column A (-1.830 versus -1.852), suggesting some mediating effects. However, that *Downgrade* remains statistically different from zero implies conference call participation does not perfectly mediate. To test the null hypothesis of no mediation effects, we use the multivariate delta method introduced by Sobel (1982, 1986) and cited by Baron and Kenny (1986), which allows us to calculate a p-value from the unit normal distribution for hypothesis testing. The test statistic that is calculated using the coefficient and standard deviation values stemming from the association between *Downgrade* and *ΔParticipate* and *ΔParticipate* and *ddACC_R* (MacKinnon & Dwyer 1993; MacKinnon, Warsi, & Dwyer 1995; Preacher and Leonardelli 2001), yields a p-value of 0.182. This implies that the mediating effect suggested by the decrease in the coefficient on *Downgrade* when moving from Column A to Column B is not statistically different from zero.[15]

Turning to timeliness, in Column C of Table 4, Panel C, we observe downgrading analysts issue forecasts with *less* delay. That is, analysts who seemingly damage their relationship with management by downgrading their stock recommendations do not suffer in terms of issuing less timely forecasts. This implies that currying favor with management does not result in more timely forecasts, rendering a formal mediation analysis of conference call access for timeliness moot. For completeness, however, we do

[15] Testing this difference using the bootstrap method of Preacher and Hayes (2004), where statistical significance for mediation effects is estimated from 3000 iterations, yields a similar p-value of 0.184.

provide in Column D the fully specified model (3d), which reveals that the effects of recommendation changes and conference call access are incremental to each other. The effects of recommendation changes tend away from zero (-1.423 vs. -1.408), not toward zero as mediation effects would predict.[16]

The negative coefficient on *Downgrade* observed in Columns C and D is somewhat puzzling. One potential explanation is that, from an empirical standpoint, downgrading may proxy more for a drop in analyst effort (McNichols and O'Brien 1997) than damage to the analyst's relationship with management. If downgrading analysts have collected less private information due to a drop in effort, forecasting based on their own private information would be easier because they have less information to process to begin with. Such an interpretation would imply downgrading analyst would also be less accurate, which we observe in Columns A and B.[17] Investigating this issue further would require shaper proxies for analyst effort over time and a direct measure of an analyst's relationship with management.

Collectively, the results of our mediation analysis do not offer compelling evidence that conference call participation is the mechanism through which currying favor with management manifests as superior private information. Rather, both changes in recommendations and changes in conference call participation are incrementally indicative of changes in the timeliness and accuracy of analyst forecasts.[18] Our inability to observe mediation effects is consistent with the superior private information of participating analysts originating before the call rather than being generated during the conference call *per se*. For regulators concerned that managers inflict punishment on analysts who issue unfavorable recommendations (Cox 2005), our evidence suggests that withholding conference call access may not appear to be the driving force that places some analysts at an *informational* disadvantage. However, we caution the reader that our empirical tests may not be sharp enough to detect mediation effects that might

[16] A test of the hypothesis that this difference in coefficients equals zero using the Sobel test cannot be rejected (p-value = 0.195.)

[17] To avoid the negative inference of analyst ability that might be associated with inaccurate forecasts, the analyst could wait and free ride on other analysts. However, free riding inflicts a different type of cost on the analyst because clients will infer that the analyst is not providing value over the other analysts who have previously forecasted (and on which the analyst is free riding).

[18] Including the interaction between *Downgrade* and *ΔParticipate* in equations (3c) and (3d) does not change our inferences and the coefficient on the interaction terms are not statistically significant. Also, the inclusion of fiscal quarter fixed effects does not change the inferences drawn from any of the changes analysis presented in Table 4.

exist, and as such we hesitate to conclude that there are absolutely no private information benefits to conference call access *per se*.[19] Moreover, withholding conference call access may hurt analysts in other ways (perhaps in terms of reputation as suggested by Libby et al. 2008) that may be of interest to regulators who are also charged with assessing factors that may drive optimistic bias into analyst stock recommendations.

5.2 Market Reactions to Analyst Forecast Revisions

Regardless of the mechanism by which participating analysts obtain superior private information, if participating analysts issue more accurate and timely forecasts relative to nonparticipating analysts, we should observe a stronger market response to participating analyst earnings forecasts. To investigate this issue, we collect Trade and Quote (TAQ) data for the observations utilized in the propensity score analysis in Table 3. We search for intraday pricing data for each observation where we have an intraday timestamp for the earnings forecast in I/B/E/S. We retain the last (first) price at least five minutes prior (subsequent) to each earnings forecast. We are able to identify pricing data for 6,336 of the control observations and 6,213 of the treatment observations.[20] We calculate the market response using absolute raw stock returns, measured as the absolute difference in the stock price before and after the forecast, divided by the stock price before the forecast.

A comparison of mean [median] absolute price responses reveals larger price responses for participating analysts (0.387%) relative to nonparticipating analysts (0.375%), but the difference is not statistically significant (p=0.302). This lack of significance may not be surprising for this subsample, however, because while we do observe that participating analysts issue more accurate forecasts (ACC_R^{post} = 52.731 vs. 52.441) in a more timely fashion (*Delay* = 12.597 vs. 13.157), these differences are not statistically significant. Thus, while the return results are directionally consistent, we are unable

[19] An alternative approach to capturing analyst information possession would be to systematically analyze the contents of the questions and answer dialog between each analyst and management (Hollander et al. 2010). Such an analysis is beyond the scope of this study and would require subjectivity in coding both the topic of the dialog and whether the answer would suggest the analyst learned something new. A more refined set of outcome variables would also likely be necessary (such as perhaps revenue forecasts in the event an analyst discusses revenue issues).

[20] Sample attrition stems from I/B/E/S not providing a time stamp on every forecast in our sample, from analysts issuing forecasts outside of NYSE trading hours, from firms not covered or having prices within the requisite window in the TAQ database.

to document statistically significant pricing effects that suggest the capital markets recognizes that participating analysts possess superior private information.

6. Conclusion

We examine the extent to which analysts who participate in earnings conference calls by asking questions possess superior private information relative to analysts who do not ask questions. Using earnings conference call transcripts to identify conference call participation, we find that initial annual earnings forecasts issued subsequent to a conference call are both more accurate and more timely for participating analysts.

We then assess whether the superior information of participating analysts stems from information disseminated during the conference call *per se* or from the information that participating analysts already possessed prior to the conference call. If the former scenario is more descriptive, we should observe call participation as the mediating factor that facilitates the association between analyst actions to curry favor with management and forecast accuracy and timeliness. Mediation analysis does not support the notion that the superior private information stems exclusively from the act of participating on the call.

Collectively, our evidence suggests that conference call participation provides an additional observable signal to identify analysts that possess relatively superior private information about a firm. However, given the economic magnitudes of the accuracy and timeliness are modest and our lack of results suggesting the conference call dialog *per se* is the driving force, regulatory intervention over conference call access on the basis of leveling the information playing field may be unwarranted.

Our inferences are subject to the caveat that some correlated omitted factors could drive the observed associations between conference call participation and forecast accuracy and timeliness. Such factors include analyst effort and pre-existing relationships between managers and analysts (Brochet et al. 2010). Our inferences are also limited by the extent to which our empirical proxies insufficiently capture the possession of superior private information by analysts, which is important given our investigation is silent on the mechanism by which analysts generate superior private information. Finally, our analysis does not explicitly examine the text of the actual dialog that accompanies participation (Hollander et al.

2010) nor do we consider other potential non-information benefits conference call access might provide to a participating analyst, such as reputation enhancement. These are important issues for future inquiry.

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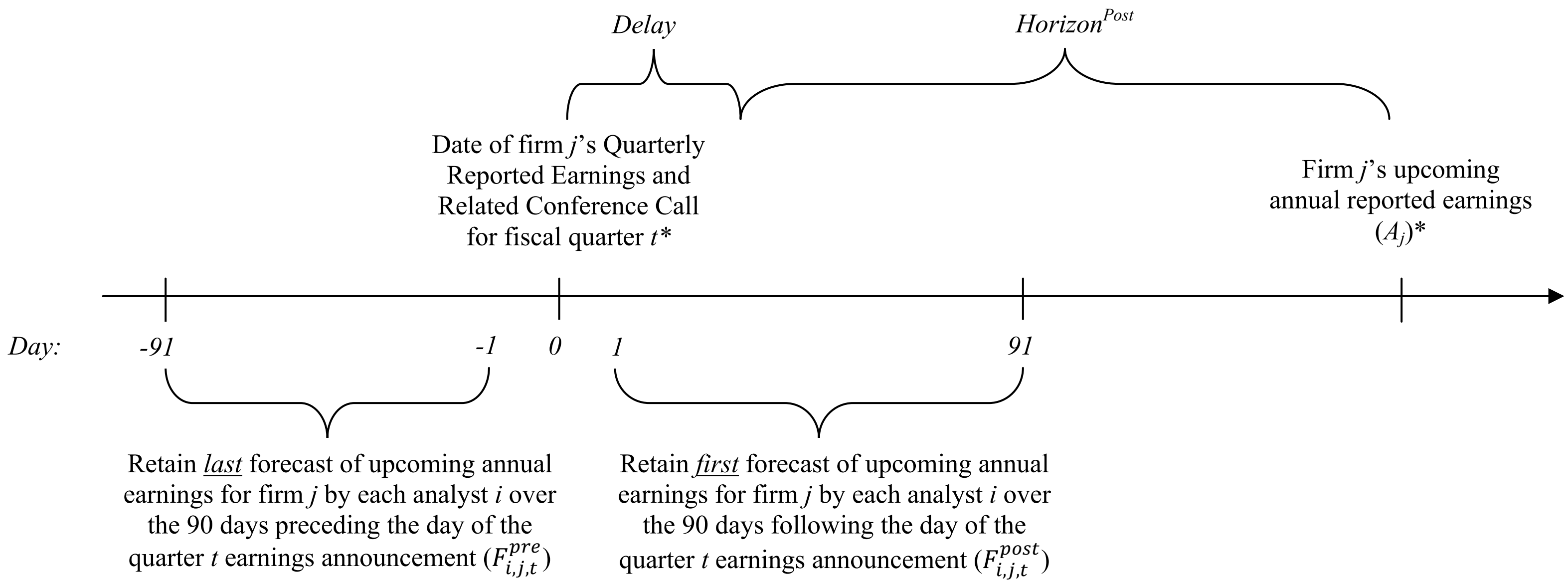
Figure 1
Timeline of Events and Measurement of Dependent Variables



$Follow_{j,t}$ = number of analysts issuing an annual earnings forecast for firm *j* at quarter *t*;
$Delay_{i,j,t}$ = number of days elapsed between announcement of earnings for fiscal quarter *t* and the issuance of $F_{i,j,t}^{post}$
$Horizon_{i,j,t}^{post}$ = number of days elapsed between the issuance of $F_{i,j,t}^{post}$ and the announcement date of fiscal year annual earnings
$absFE_{i,j,t}^{pre} = |A_j - F_{i,j,t}^{pre}|$
$absFE_{i,j,t}^{post} = |A_j - F_{i,j,t}^{post}|$
$absFErank_{i,j,t}^{pre}$ = rank from 1 to *n* of $absFE_{i,j,t}^{pre}$, where *n* equals *Follow*, and the smallest (largest) absolute forecast error receives value of 1 (*n*).
$absFErank_{i,j,t}^{post}$ = rank from 1 to *n* of $absFE_{i,j,t}^{post}$, where *n* equals *Follow*, and the smallest (largest) absolute forecast error receives value of 1 (*n*).
$ACC\_R_{i,j,t}^{pre} = 100 - \frac{absFErank_{i,j,t}^{pre} - 1}{Follow_{j,t} - 1} x100$ = standardized accuracy ranking for $FE_{i,j,t}^{pre}$ between 0 (for least accurate) and 100 (for most accurate)
$ACC\_R_{i,j,t}^{post} = 100 - \frac{absFErank_{i,j,t}^{post} - 1}{Follow_{j,t} - 1} x100$ = standardized accuracy ranking for $FE_{i,j,t}^{post}$ between 0 (for least accurate) and 100 (for most accurate)
$\Delta ACC\_R_{i,j,t} = ACC\_R_{i,j,t}^{post} - ACC\_R_{i,j,t}^{pre}$
$ddACC\_R_{i,j,t} = \Delta ACC\_R_{i,j,t} - \Delta ACC\_R_{i,j,t-1}$
$\Delta Delay_{i,j,t} = Delay_{i,j,t} - Delay_{i,j,t-1}$
*Note that for the fourth fiscal quarter earnings call in year *t*, relative accuracy of annual earnings prior to and subsequent to Q4 earnings is for year *t+1*.

Table 1
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 within 90 days *after* the day of firm *t*'s earnings announcement and conference call. Following Ke and Yu (2006), estimates range between zero and 100: *ACC_R*^{post} = 100 - ((*absFErank*^{post} - 1)/(*Follow* - 1))*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 within 90 days *before* the day of quarter *t*'s earnings announcement and conference call. Following Ke and Yu (2006), estimates range between zero and 100: *ACC_R*^{post} = 100 - ((*absFErank*^{pre} - 1)/(*Follow* - 1))*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.
AllStar	Indicator variable that equals one if the analyst made any of the Institutional Investor Research All-American teams as of the most recent prior year, and zero otherwise.
Participate	*Participate* in the current quarter minus *Participate* in the prior quarter for a given analyst on adjacent quarters for a given firm.
ΔACC_R	ACC_R^{post} - ACC_R^{pre}
ΔACC_R^{pre}	$ACC\_R^{pre}{}_{i,j,t}$ - $ACC\_R^{pre}{}_{i,j,t-1}$
ddACC_R	$\Delta ACC\_R_{i,j,t}$ - $\Delta ACC\_R_{i,j,t-1}$
Broker_R	is the relative size of the brokerage house employing analyst *i* at the time of the quarter *t* earnings announcement, defined as $100-\frac{Broker\_revrank_{i,j,t}-1}{Follow_{i,j,t}-1}x100$, 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.
ΔBroker_R	$Broker\_R_{i,j,t} - Broker\_R_{i,j,t-1}$
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 the date of firm *j*'s quarterly earnings conference call and the issuance of analyst *i*'s first one-year-ahead annual earnings forecast subsequent to the conference call date.
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 $100-\frac{F\_Exper\_revrank_{i,j,t}-1}{Follow_{i,j,t}-1}x100$, where *F_Exper_revrank* is the reverse ranking of *F_Exper*.
ΔF_Exper_R	$F\_Exper\_R_{i,j,t} - F\_Exper\_R_{i,j,t-1}$
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 unsplit-adjusted detail file.
FE_p	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 $100-\frac{Firms\_revrank_{i,j,t}-1}{Follow_{i,j,t}-1}x100$, where *Firms_revrank* is the reverse ranking of *Firms*.
ΔFirms_R	$Firms\_R_{i,j,t} - Firms\_R_{i,j,t-1}$

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 $100 - \frac{ForFreq\_revrank_{i,j,t} - 1}{Follow_{i,j,t} - 1} x100$, where *ForFreq_revrank* is the reverse ranking of *ForFreq*.

ΔForFreq_R $ForFreq\_R_{i,j,t} - ForFreq\_R_{i,j,t-1}$

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*.

ΔLnFollow $LnFollow_{i,j,t} - LnFollow_{i,j,t-1}$

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 $100 - \frac{Horizon^{post}\_revrank_{i,j,t} - 1}{Follow_{i,j,t} - 1} x100$, where $Horizon^{post}\_revrank$ is the reverse ranking of $Horizon^{post}$.

$ΔHorizon\_R^{post}$ $Horizon\_R^{post}{}_{i,j,t} - Firms\_R^{post}{}_{i,j,t-1}$

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 $100 - \frac{Inds\_revrank_{i,j,t} - 1}{Follow_{i,j,t} - 1} x100$, 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.

PriorParticipate 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 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 $100 - \frac{T\_Exper\_revrank_{i,j,t} - 1}{Follow_{i,j,t} - 1} x100$, where *T_Exper_revrank* is the reverse ranking of *T_Exper*.

ΔT_Exper_R $T\_Exper\_R_{i,j,t} - T\_Exper\_R_{i,j,t-1}$

Table 2
Descriptive Statistics for 56,907 Analyst Firm Quarter Observations

Variable[a]	**Mean**	**Median**	**Std Dev**	**Min**	**Max**
ACC_R^{post}	52.747	53.846	29.432	0.000	100.000
Delay	13.465	1.000	24.477	1.000	91.000
Participate	0.473	0.000	0.499	0.000	1.000
SBuy	0.208	0.000	0.406	0.000	1.000
Buy	0.254	0.000	0.436	0.000	1.000
Sell	0.062	0.000	0.241	0.000	1.000
SSell	0.022	0.000	0.146	0.000	1.000
QAmin	35.584	35.333	13.805	0.000	125.767
LnFollow	3.343	3.434	0.776	1.099	4.868
AllStar	0.141	0.000	0.348	0.000	1.000
ACC_R^{pre}	52.529	53.333	29.515	0.000	100.000
F_Exper_R	51.008	50.000	28.429	0.000	100.000
T_Exper_R	51.112	50.833	29.387	0.000	100.000
Inds_R	36.308	32.353	22.833	0.000	100.000
ForFreq_R	50.623	50.000	28.856	0.000	100.000
Broker_R	49.283	50.000	29.904	0.000	100.000
Firms_R	49.740	50.000	29.439	0.000	100.000
CCuser	1.842	1.000	2.048	0.000	14.000
PriorParticipate	0.609	1.000	0.488	0.000	1.000
RecHorizon	219.311	158.000	207.280	1.000	1886.000

Table 3
Propensity Score Analysis

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

$$Participate_{i,j,t} = \beta_0 + \beta_1 SBuy_{i,j,t} + \beta_2 Buy_{i,j,t} + \beta_3 Sell_{i,j,t} + \beta_4 SSell_{i,j,t} + \beta_5 QAmin_{i,j,t} + \beta_6 LnFollow_{i,j,t} + \beta_7 AllStar_{i,j,t} + \beta_8 ACC\_R^{pre}_{i,j,t} + \beta_9 F\_Exper\_R_{i,j,t} + \beta_{10} T\_Exper\_R_{i,j,t} + \beta_{11} Inds\_R_{i,j,t} + \beta_{12} ForFreq\_R_{i,j,t} + \beta_{13} Broker\_R_{i,j,t} + \beta_{14} Firms\_R_{i,j,t} + \beta_{15} CCuser_{i,j,t} + \beta_{16} PriorParticipate_{i,j,t} + \beta_{17} RecHorizon_{i,j,t} + \upsilon_{i,j,t}.$$

Variable[a]	**Predicted Sign**[e]	**Coefficient**[b]		**Standard Error**[c]
Intercept	?	-0.286	***	0.081
SBuy	+	0.418	***	0.032
Buy	+	0.396	***	0.028
Sell	-	-0.183	***	0.046
SSell	-	-0.325	***	0.080
QAmin	+	0.016	***	0.001
LnFollow	-	-0.519	***	0.019
AllStar	+	0.097	*	0.051
ACC_R^{pre}	+	0.000		0.000
F_Exper_R	+	0.003	***	0.001
T_Exper_R	+	-0.002	***	0.001
Inds_R	-	-0.004	***	0.001
ForFreq_R	+	0.001	*	0.000
Broker_R	+	0.006	***	0.001
Firms_R	-	-0.005	***	0.001
CCuser	+	0.206	***	0.011
PriorParticipate	+	1.388	***	0.036
RecHorizon	-	0.000	***	0.000
Sample size[d]		56,907		
Psuedo R^2		14.23%		
Log Likelihood		-33,760.32		
Wald χ^2		3082.99		

Table 3 (continued)

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 (N=26,510)

	Treatment (*Participate* = 1)		Control (*Participate* = 0)		Differences		P value of differences	
Variable[a]	**Mean**	**Median**	**Mean**	**Median**	**Mean**	**Median**	**Mean**	**Median**
Propensity Score	0.512	0.532	0.512	0.531	0.000	0.001	0.970	0.970
ACC_R^{post}	53.133	54.412	52.437	53.333	0.696	1.079	0.050	0.060
Delay	12.847	1.000	13.830	2.000	-0.983	-1.000	0.000	0.000
Sample size[d]	13,255		13,255					

Panel C: Average Relative Forecast Accuracy (ACC_R^{post}) by Timeliness and Participation for Propensity Score Matched Sample (N=26,510)

	COLUMN A *Participate* = 1	*COLUMN B* *Participate* = 0
ROW 1: Delay >1	53.953 (N=5,927)	53.073 (N=6,774)
ROW 2: Delay <=1	52.470 (N=7,328)	51.771 (N=6,481)

P-value for test Row 1 Column A = Row 2 Column B: <0.001

P-value for test Row 2 Column A = Row 1 Column B: 0.226

[a] See Table 1 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 2 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. This results in a sample for propensity score analysis of 13,255 x 2 = 26,510.

[e] Predicted signs are taken from Mayew (2008).

Table 4

OLS regression investigating the association between relative forecast accuracy and timeliness changes as a function of conference call participation changes

Panel A: Descriptive Statistics for Change Variables (N=24,073)

Variable[a]	Mean	Median	Std Dev	Min	Max
Variables of Interest					
ddACC_R	0.272	0.000	43.903	-179.167	174.000
ΔDelay	0.694	0.000	29.522	-90.000	90.000
ΔParticipate	0.007	0.000	0.547	-1.000	1.000
% obs ΔParticipate > 0	15.3%				
% obs ΔParticipate < 0	14.7%				
% obs ΔParticipate = 0	70.0%				
Downgrade	0.101	0.000	0.302	0.000	1.000
Control variables					
ΔF_Exper_R	3.708	0.000	11.541	-71.818	82.432
ΔT_Exper_R	2.389	0.000	8.191	-66.364	52.778
ΔLnFollow	-0.099	0.000	0.421	-3.076	1.992
ΔFirms_R	0.163	0.000	13.594	-100.000	90.000
ΔBroker_R	0.094	0.000	7.969	-97.917	75.000
ΔForFreq_R	7.937	6.910	19.706	-77.500	90.000
$\Delta Horizon\_R^{post}$	-9.504	-25.000	39.969	-100.000	100.000
ΔACC^{pre}	5.526	13.333	40.472	-100.000	100.000

Panel B: Association between Conference Call Participation Changes and Forecast Accuracy and Timeliness Changes

$$ddACC\_R_{i,j,t} = \delta_0 + \delta_1\, \Delta Participate_{i,j,t} + CONTROLS + \mu_{i,j,t} \qquad (3a)$$

$$\Delta Delay_{i,j,t} = \gamma_0 + \gamma_1\, \Delta Participate_{i,j,t} + CONTROLS + \eta_{i,j,t} \qquad (3b)$$

	(A)	(B)	(C)	(D)
Dependent Variable:	*ddACC_R*	*ddACC_R*	*ΔDelay*	*ΔDelay*
Intercept	-0.264	0.652***	0.699***	-0.210
	(0.286)	(0.317)	(0.202)	(0.239)
ΔParticipate	1.225**	1.205**	-0.847**	-0.788**
	(0.513)	(0.513)	(0.360)	(0.359)
Control Variables:				
ΔF_Exper_R		0.010		-0.003
		(0.036)		(0.025)
ΔT_Exper_R		0.020		-0.077**
		(0.050)		(0.036)
ΔLnFollow		-0.542		4.528***
		(0.680)		(0.545)
ΔFirms_R		-0.009		-0.007
		(0.023)		(0.015)
ΔBroker_R		-0.001		0.021
		(0.037)		(0.031)
ΔForFreq_R		0.002		0.097***
		(0.015)		(0.010)
$\Delta Horizon\_R^{post}$		-0.080***		N/A[d]
		(0.007)		
ΔACC^{pre}		N/A[d]		-0.020***
				(0.005)
Adjusted R^2	0.02%	0.57%	0.02%	0.97%
# of analyst-firm-quarter observations	24,073	24,073	24,073	24,073

Panel C: Mediating Effects of Recommendation Changes

$$ddACC\_R_{i,j,t} = \delta_0 + \delta_1\, \Delta Participate_{i,j,t} + \delta_2\, Downgrade_{i,j,t} + CONTROLS + \mu_{i,j,t} \quad (3c)$$

$$\Delta Delay_{i,j,t} = \gamma_0 + \gamma_1\, \Delta Participate_{i,j,t} + \gamma_2\, Downgrade_{i,j,t} + CONTROLS + \eta_{i,j,t} \quad (3d)$$

	(A)	(B)	(C)	(D)
Dependent Variable:	*ddACC_R*	*ddACC_R*	*ΔDelay*	*ΔDelay*
Intercept	-0.459	0.469	-0.076	-0.069
	(0.286)	(0.330)	(0.246)	(0.246)
ΔParticipate		1.194**		-0.797**
		(0.513)		(0.359)
Downgrade	-1.852***	-1.830**	-1.408**	-1.423**
	(0.928)	(0.928)	(0.637)	(0.637)
Control Variables	Included	Included	Included	Included
Adjusted R^2	0.57%	0.59%	0.97%	1.00%
# of analyst-firm-quarter observations	24,073	24,073	24,073	24,073

[a] See Table 1 for variable definitions.
[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 two way clustering by analyst and the calendar quarter in which the conference call was held.
[d] Control variable not applicable because due to a mechanical association with the dependent variable.