The role of gender in the aggressive questioning of CEOs during earnings conference calls

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ABSTRACT

We investigate the role of gender on the aggressiveness of sell-side analysts' questions during earnings conference calls. Our tests reveal that the verbal aggressiveness of analysts' questions is significantly associated with both the gender of the analyst asking the question and the gender of the CEO fielding the question. First, we find that male analysts are more verbally aggressive than female analysts. Specifically, male analysts' questions are more direct and more likely to be followed with further questions, to have a preface statement, and to be negative, all of which are consistent with verbal aggressiveness. Second, male analysts' questions to female CEOs are more aggressive than their questions to male CEOs. Gender-based verbal aggressiveness appears to be associated with analysts' career trajectories: Female analysts who ask aggressive questions have a higher likelihood of becoming "star" analysts, whereas we fail to find such evidence for male analysts.

Keywords: Earnings conference calls, gender, gender differences, question style, verbal aggressiveness

JEL classification: D83, J16, M14, M40, M41, Z13

I INTRODUCTION

We investigate whether gender is associated with the verbal aggressiveness of analysts' questions to CEOs during quarterly earnings conference calls. The term "verbal aggressiveness" originates in the political science literature and measures how challenging questions are (e.g., Clayman and Heritage 2002; Clayman, Heritage, Elliott, and McDonald 2007). First, we examine whether questions asked by male analysts are more or less verbally aggressive, in general, than questions asked by female analysts. We then consider whether the gender of the CEO affects analysts' questions. Specifically, we explore whether male analysts pose more aggressive questions to female CEOs than to male CEOs, consistent with patterns of verbal aggression in male/female conversations that have been observed in prior research (e.g., Zimmerman and West 1975). Finally, we investigate whether verbal aggressiveness is associated with the likelihood of males or females being named to *Institutional Investor*'s All-America Research Team.

Earnings conference calls are high-stakes settings both for firms and analysts. Prior research finds that conference calls have capital market consequences for firms (e.g., Bushee, Matsumoto, and Miller 2004; Lee 2016) because they provide relevant information to the market (Brown, Hillegeist, and Lo 2004). For analysts, conference calls (particularly the Q&A) are an important source of information for earnings forecasting (Brown, Call, Clement, and Sharp 2015)—an important part of their jobs (Hong and Kubik 2003)[1]—and can affect their career trajectories (Hong and Kubik 2003), including their chances of becoming All-American analysts (Stickel 1992).

For analysts, asking verbally aggressive questions may be a crucial tool for getting more information from managers. However, verbal aggressiveness may come at a cost, because analysts'

[1] In the survey of Brown et al. (2015), 58.79 percent of analysts stated that the Q&A portion of earnings conference call is a very useful information outlet for their earnings forecasting process.

behavior within conference calls can affect their career outcomes (Cen, Chen, Dasgupta, and Ragunathan 2021).[2] Specifically, being verbally aggressive may run against established norms of politeness in interactions (Goffman 1967; Clayman and Heritage 2002), and analysts who ask unfavorable questions may lose access to private information channels to management (Mayew, Sharp, and Venkatachalam 2013; Milian, Smith, and Alfonso 2017; Cen et al. 2021).[3] This risk may be especially high for female analysts, as they are more likely to view private communications with management as an important information source (Brown, Call, Clement, and Sharp 2016).

Prior studies suggest that gender matters for communication in earnings conference calls. Milian et al. (2017) find that, during conference calls, female analysts have a more positive tone and are more likely to praise management. Francis, Shohfi, and Xin (2020) find that female analysts' tone is more positive, they are less vague, they use less numerical content, make fewer hesitations in their speech, and engage in less back-and-forth with management. De Amicis, Falconieri, and Tastan (2021) find that female analysts are more positive and less vague (and that analysts' comments to female CEOs are less positive and more vague). These findings complement earlier research showing that women, in general, tend to use polite forms of language (e.g., Lakoff 1975) and suggest that female analysts might be less verbally aggressive than male analysts.

However, given that female analysts have self-selected into a male-dominated profession, one might also expect their verbal aggressiveness to be more in line with that of male analysts (Kumar 2010). Indeed, prior studies on verbal aggressiveness and gender in a professional setting

[2] Cen et al. (2021) find that early conference call participation (i.e., being among the first to ask a question during the Q&A) is associated with analysts' likelihood to find a new job faster and to find a higher-quality job in the event of a brokerage closure, emphasizing the importance of conference call participation for analyst career outcomes.
[3] Specifically, Milian et al. (2017) suggest that analysts with a more positive tone have better access to management and might be better able to extract private information from them. Consistent with this, Cen et al. (2021) argue that access to management could reflect a reciprocal quid pro quo relationship (i.e., analysts' access to management depends on how favorable their behavior is to management). Lastly, Mayew et al. (2013) state that management has discretion over which analysts are allowed to ask questions during conference calls and that analysts who are denied opportunities to ask questions have an informational disadvantage.

(journalists in U.S. presidential news conferences) find that women are *more* verbally aggressive than men in periods when male journalists are predominant in presidential press conferences (Clayman 2004; Clayman, Elliott, Heritage, and Beckett 2012; Clayman, Heritage, and Hill 2020).[4] Clayman et al. (2020) argue that their finding is consistent with "Avis syndrome," in which women who work in male-dominated professions feel pressure to try harder (e.g., Sherman and Rosenblatt 1984). Clayman et al. (2012) attribute a similar finding to "some combination of self-selection into this role, the preferences of occupational gatekeepers, and on-the-job pressures to overperform." Because earnings conference calls are another setting where women are in the minority (11.6 percent of our sample), we could find a similar pattern here.

There are three key findings in this paper. First, we find that male analysts' questions are more verbally aggressive than female analysts' questions. Second, this difference is more pronounced when the CEO is female – in line with a gender-based out-of-group bias. Third, verbally aggressive female analysts, unlike verbally aggressive male analysts, are more likely to be listed as top-three analysts on *Institutional Investor*'s annual list of best analysts. Our findings are interesting because verbal aggressiveness is a different construct than positive tone or praise words – two constructs that have been investigated in other studies – and is new to the accounting literature. While one might argue that the use of negative words (or the lack of positive and praise words) is adversarial, our verbal aggressiveness measures seem to pick up more than just sentiment. Consistent with this, praise words and tone are only weakly correlated with verbal aggressiveness.[5]

[4] Over time, the percentage of female journalists in presidential press conferences has grown steadily (from around 10 percent of the sample in the 1950s to around 40 percent by the end of the 1990s) and differences between verbal aggressiveness in male and female journalists have been attenuated (Clayman et al. 2012; Clayman et al. 2020).

[5] Depending on the verbal aggressiveness measure, the Pearson correlation of verbal aggressiveness with praise words (positive words) is low (ranging between -0.076 and 0.090 (between -0.056 and 0.010) depending on the verbal aggressiveness measure). Consistent with the low Pearson correlations between analysts' use of praise words and the verbal aggressiveness measures, fifty-two percent of analyst questions that use praise words also use verbally aggressive language; questions that do not use praise words use verbally aggressive language 50 percent of the time.

Nevertheless, to ensure that we are picking up an incremental effect, we rerun our main tests after excluding all questions with a negative net tone and continue to find similar results. In addition, the use of positive and negative words by analysts is relatively uncommon.[6] In contrast, the four verbal aggressiveness measures we use are relatively common: depending on the measure, analysts use them in 14.5–78.8 percent of the questions in our sample.[7]

Our findings make several contributions to the literature. First, our finding that earnings conference call questions from male sell-side analysts tend to be more verbally aggressive contributes to the literature on gender and analysts (e.g., Green, Jegadeesh, and Tang 2009; Kumar 2010; Li, Sullivan, Xu, and Gao 2013; Milian et al. 2017). Second, our finding that male analysts ask more aggressive questions of female CEOs contributes to the literature on cross-gender communications. Third, our paper contributes to the literature on out-of-group bias between analysts and CEOs. Specifically, we add to Jannati, Kumar, Niessen-Ruenzi, and Wolfers (2020), who provide evidence that male analysts make lower earnings forecasts for firms headed by female CEOs (which is consistent with an out-of-group bias). Fourth, we contribute to the literature on verbal aggressiveness, which has been a focus of prior research in political science (Clayman and Heritage 2002; Clayman et al. 2007), economics (Dupas, Modestino, Niederle, and Wolfers 2021), and

[6] We find that, in our sample, analysts only use 4.456 positive and 1.596 negative words for every 100 words spoken (using the positive and negative word lists of Bozanic, Chen, and Jung (2019), which were derived from analyst reports). Milian et al. (2017) find even smaller numbers (1.502 positive and 1.04 negative words per 100 words spoken), likely due to their use of a different dictionary. If we use the Loughran and McDonald (2011) lists of positive and negative words, which are derived from 10-Ks, we obtain similar frequencies as Milian et al. (2017): 1.435 positive words and 1.299 negative words per 100 words spoken by an analyst.

[7] We do observe some instances where analysts use praise words and positive words while being verbally aggressive. For instance, David Magee from Suntrust Robinson Humphrey starts his question in the Q1 2008 conference call of Fred's Inc. by praising management and using a positive tone in his initial speech turn: "Good morning, guys, and congratulations on the better numbers." After management thanked him, he subsequently uses a preface statement and begin asking direct questions: "Just a question regarding more of a bigger picture longer term question. Look at your operating margins this year, I got a number around 2.5% built in our forecast, I'm looking at that number versus your peak a few years ago close to 4%. Your gross margins are about the same. It looks more like an expense ratio opportunity there. Do you see anything that's structural that prevents you from getting back to that 4% level or even higher over time?"

communications (Banning and Billingsley 2007). Our final contribution is our evidence that gender-related verbal aggressiveness is associated with the likelihood that male or female analysts are voted top-three All-American analysts.

We use four measures of verbal aggressiveness from Clayman and Heritage (2002): follow-up questions, preface statements, negative questions, and directness.[8] Follow-up questions indicate that the analyst was not satisfied with the initial answer. They are used to gather more information and narrow the scope of the response. Preface statements precede the question and put it into context. This frees the questioner from the previous context and allows for more challenging questions. Negative questions begin with phrases like "isn't it" or "wouldn't you" and are viewed more as assertions than questions (Heritage 2002). Indirect questions use a self-reference (e.g., "may I") or other-reference (e.g., "could you"), which makes the question easier to defer, and therefore weaker. Consequently, directness captures questions that lack self- and other-references. We provide examples of each type of verbal aggressiveness in Appendix 1.

Our analysis is based on quarterly earnings conference call transcripts from 2005 to 2018 for US companies. We focus on a) the Q&A section of earnings conference calls, because the management discussion section does not involve interaction, and b) questions asked to CEOs, which are the vast majority (78 percent) of the questions in our sample. To determine the genders of CEOs and analysts, we enter their names into the gender estimation tool provided by Gender API (gender-api.com). Gender API comprises almost 2,000,000 international names and has been widely used by prior research to estimate gender (Caplar, Tacchella, and Birrer 2017). Using this

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[8] Verbal aggressiveness in psychology refers to language that is intended to attack the self-concept of the other party (Aloia and Solomon, 2017). Such language takes forms such as name-calling (David and Kistner 2000) and insults and yelling (Salmivalli and Kaukiainen 2004) and occurs primarily in non-professional settings. In contrast, the verbal aggressiveness that is studied in communications and political science is used to proxy for disagreement or being critical in professional settings such as presidential press conferences (Clayman et al. 2020). We focus on the type of verbal aggressiveness studied by Clayman et al. (2020) in this study.

data, we can investigate how the aggressiveness of the questions to CEOs varies depending on the CEO's gender and the gender of the analyst asking the question.

We start our analysis by comparing the verbal aggressiveness of male vs. female analysts' questions. We find that male analysts' questions are more likely to be verbally aggressive (i.e., be followed with further questions, have a preface statement, lack a self-reference or other-reference, and be negative and push for a yes/no response). Moreover, we find that the verbal aggressiveness of questions by male analysts is more pronounced when the CEO is female. Our results hold after including the inverse Mills' ratio to correct for potential selection bias in the choice of the CEO, after excluding questions with a negative tone, and after controlling for firm-level and analyst-level characteristics. Finally, we find that verbally aggressive questions are associated with a higher likelihood of female – but not male – analysts becoming All-American analysts.

II LITERATURE REVIEW

Gender and analysts

Prior research on differences in the forecast accuracy of male and female analysts is mixed. Green et al. (2009) find that female analysts produce less accurate forecasts, but Kumar (2010) finds that they produce more accurate ones. Green et al. and Kumar have different samples because of differing time frames (1995–2005 vs. 1983–2006, respectively), matching criteria (e.g., Kumar requires CRSP data), and how they determine gender (Green et al. use Nelson's and Kumar uses Nelson's, Yahoo Finance, Factiva, and Google), which may account for their opposing results. However, research consistently finds that female analysts are more likely to become "star" analysts (Green et al. 2009; Li et al. 2013) and to be promoted (Kumar 2010; Li et al. 2013).

In our study, we investigate whether male analysts ask more aggressive or less aggressive questions relative to female analysts, whether CEO gender matters to the aggressiveness of analysts' questions, and whether verbal aggressiveness is associated with different consequences for male and female analysts in the context of All-American analyst voting. To our knowledge, no other study has investigated these questions, but some related work has been done on the role of gender in questions asked in professional settings. In conference calls, Milian et al. (2017) find that female analysts have a more positive tone and are more likely to praise management. And De Amicis et al. (2021) find that female analysts are more positive and less vague. They also find that analysts are less positive and more vague when speaking to female CEOs. Finally, Francis et al. (2020) find that female analysts' have a more positive tone, use less vague language, hesitate less, and engage in less back-and-forth with management. There is no previous study on the verbal aggressiveness of male vs. female analysts in conference calls.

However, journalists asking questions in presidential press conferences is a setting that shares some similarities with earnings conference calls (i.e., they are both turn-based, the questioner is called upon, the stakes are high, etc.). Studies from the political science literature find that in presidential press conferences, female journalists are more verbally aggressive in periods when men are in a strong majority (Clayman 2004; Clayman et al. 2012; Clayman et al. 2020). This may be due to female journalists self-selecting into the field and perhaps feeling the need to show that they are trying harder than male journalists (Clayman et al. 2012; Clayman et al. 2020).

The gender of who is being asked questions also matters in professional settings. For example, Dupas et al. (2021) find that women are asked more questions and more hostile questions than men in economics job talks. Kanze, Huang, Conley, and Higgins (2018) detect a gender bias in the questions that investors ask female entrepreneurs at startup funding events. Specifically, they find that male entrepreneurs tend to be asked promotion-focused questions and female entrepreneurs tend to be asked prevention-focused questions. This is significant because entrepreneurs who are asked the former type of questions are able to raise significantly higher amounts of funds.

Analysts' questions during earnings conference calls

We focus on the Q&A section of earnings conference calls because we are interested in analysts' questions. Past research has investigated why analysts ask certain types of questions and the likelihood of their asking a question. For example, analysts are more likely to ask negative questions when firms miss earnings expectations (Graham, Harvey, and Rajgopal 2005). In addition, the probability of an analyst asking a question during an earnings conference call increases with the favorableness of the analyst's outstanding stock recommendations (Mayew 2008). Whether an analyst's question occurs close to the beginning of the Q&A section is also important, because early participation in conference calls may be a proxy for connectivity to management.[9]

In addition to investigating the timing of analysts' questions, researchers have considered the questions' tone. Chen, Nagar, and Schoenfeld (2018) find that the tone of analysts' questions appears to affect securities prices. Brockman, Li, and McKay (2015) find that managers have a more optimistic (less pessimistic) tone than analysts. Consistent with this, investors (especially institutional investors) react more strongly to analyst tone than to managerial tone. Managerial tone and analyst tone appear to capture expectations of good and bad news for the firm: Brockman, Cicon, Li, and Price (2017) find that corporate insiders buy (sell) company shares following negative (positive)-tone conference calls (although investors do not seem to be able to discern the strategic use of tone), and Huang, Teoh, and Zhang (2014) find that abnormal tone predicts lower future earnings.

Finally, in addition to tone, recent research has investigated praise. The amount of praise that analysts lavish on managers in conference calls is associated with earnings surprises as well as earnings announcements and next quarter's abnormal stock returns (Milian and Smith 2017).

[9] Cen et al. (2021) find that analysts who (are allowed to) speak earlier in the Q&A session of earnings calls are more successful in the labor market than are peers from the same brokerage when their brokerage firm closes.

III THEORETICAL BACKGROUND AND HYPOTHESIS DEVELOPMENT

Prior research suggests that managerial characteristics, including gender, having an accounting or financial education, having an MBA or law degree, and working as an auditor, consultant, or investment banker, affect managers' tone in conference calls (Davis, Ge, Matsumoto, and Zhang 2015). In addition, Brochet, Miller, Naranjo, and Yu (2019) find that managers from individualistic cultures use a more positive tone in conference calls. Gender is one of the personal characteristics that can impact how managers and analysts communicate (e.g., Milian et al. 2017; Francis et al. 2020; De Amicis et al. 2021). For example, psychology research finds that women are generally more polite (Hartman 1976), more likely to hedge (Crosby and Nyquist 1977), more likely to use adverbs and personal pronouns, and more likely to use disclaimers in their speech (Lakoff 1975). Consistent with this, research suggests that gender is associated with analysts' tone during conference calls. For example, several studies (e.g., Milian et al. 2017; Francis et al. 2020; De Amicis et al. 2021) find that female analysts' tone is more positive than male analysts' tone. Finally, Milian et al. (2017) find that the favorableness of female analysts' questions to management affects their ability to ask questions in the future.

In addition to tone, analysts may differ across genders in how verbally aggressive they are. We investigate analysts' verbal aggressiveness using four measures from the political science literature (e.g., Clayman and Heritage 2002).[10] First, we include the frequency of follow-up questions asked. In our context, follow-up questions occur when analysts ask another question after the CEO has replied to their first. Follow-up questions are considered aggressive because they violate

[10] Clearly, the context in earnings conference calls differs from that of the presidential press conferences studied in Clayman and Heritage (2002). Consequently, some of their measures are not applicable to our setting and were not included in our study. For example, Clayman and Heritage (2002) coded openly hostile questions (hostility measures whether the questioner is blatantly critical) as aggressive. Not only are these types of questions rare in conference calls, but the classification is also subjective and must be hand-collected. Given the large sample, this is not feasible in our study.

the one-turn norm in conversations (Clayman 1993; Heritage and Greatbatch 1991). They imply that the questioner does not accept the prior response as adequate and is asking for further details (Clayman, Elliott, Heritage, and McDonald 2006). Roughly two-thirds of the analysts ask follow-up questions in our sample.[11] Second, we include the use of preface statements. Preface statements precede the question and put it into context. By introducing a context, the questioner frees themselves from the previous context, which allows them to ask more challenging questions (Clayman 1993) and introduce negative information (Heritage 2002). Third, we include the use of direct questions. Direct questions *do not* begin with self-referencing phrases like c*an I*, c*ould I*, and *may I* or other-referencing phrases like c*an you*, c*ould you*, w*ill you*, and w*ould you*. Questions that begin with those phrases are deferential – akin to asking for permission – and make the questioner appear less dominant (Clayman and Heritage 2002). Clayman et al. (2007) measure aggressiveness by the lack of self-references (directness). We also include a lack of other-references in the measure. Finally, following Clayman and Heritage (2002), we code questions that begin with phrases such as *isn't it* or *aren't you* as aggressive, as these questions are close to assertions.

Given prior research that finds female analysts' tone is more positive than male analysts' in earnings conference calls and that women, in general, tend to be more polite (e.g., Lakoff 1975; Hartman 1976) and more risk averse (e.g., Barua, Davidson, Rama, and Thiruvadi 2010; Francis, Hasan, and Wu 2013; Francis, Hasan, Wu, and Yan 2014), we might expect female analysts to be

[11] Based on an extensive manual screening of conference call transcripts, we identified few calls where analysts were explicitly instructed to ask only one question each. In such a setting, we would not capture the question style of analysts but rather the question guidance by the firm holding the call. Unfortunately, these instructions are not mentioned separately in the transcripts – they are buried among other types of "operator instructions." We believe that this does not bias our estimates, because it would lead to a lack of variation for male and female analysts alike, as both would be limited to one question each. This would make it more difficult to reject the null hypothesis. In any case, only 4.87 percent of calls have no follow-up questions.

less verbally aggressive than male analysts.[12] On the other hand, women who work as analysts may be less likely to conform to these stereotypes, as they have self-selected into a male-dominated profession. Kumar (2010) finds that women self-select into careers as analysts (in line with prior research arguing that women self-select into male-dominated professions in general (Lemkau 1983) and that female analysts tend to be women who are less risk averse than other women and are often more capable than men.

Clayman et al. (2012) suggest that a combination of self-selection into a male-dominated profession, the "Avis syndrome,"[13] and industry norms may lead to women working in journalism being more verbally aggressive. Consistent with this, in periods when the media covering presidential press conferences was more male-dominated, female journalists asked more verbally aggressive questions. As the proportion of females has increased over time, the effect has been attenuated (Clayman 2004; Clayman et al. 2020). Presidential press conferences and earnings conference calls are similar in that they are both high stakes settings with highly skilled people asking questions. However, analyst coverage in earnings conference calls has been and continues to be more male-dominated. Overall, it is unclear a priori whether we should expect higher levels of verbal aggressiveness from male analysts or from female analysts.

Studies on mixed-gender communications outside of conference calls find that women speak more hesitantly when addressing men, but not vice versa (e.g., Carli 1990). In addition, men interrupt women more often than men (Zimmerman and West 1975). Interruptions of women by men are more often negative (e.g., they involve disagreement), particularly when men have more

[12] Consistent with this is research in psychology that suggests that women and men communicate differently and that men are more aggressive verbally than women are (e.g., David and Kistner 2000; Salmivalli and Kaukiainen 2004) and that men see this as more appropriate than women do (Aloia and Solomon 2017).
[13] Women who work in male-dominated professions may feel pressure to work harder - the "Avis syndrome" (e.g., Sherman and Rosenblatt 1984).

influence in the group (Mendelberg, Karpowitz, and Oliphant 2014). Moving to a professional setting, Blair-Loy et al. (2017) find that women face more follow-up questions and interruptions in job talks for "masculine-typed" jobs.[14] These results are consistent with an out-of-group bias.

There is evidence already of out-of-group gender biases in analysts' interactions with management in the earnings conference call setting. Specifically, Jannati et al. (2020) find that male analysts make lower earnings forecasts for firms with female CEOs. This finding, together with research suggesting that women are perceived as less knowledgeable (Ng, Brooke, and Dunne 1995) and that women's knowledge is discounted by men (Huckfeldt, Sprague, Kuklinski, and Wyer 1995), suggests that an out-of-group bias by men towards women is likely to manifest itself in our measures of verbal aggressiveness. Specifically, we expect male analysts to be more verbally aggressive when they question female CEOs than when they question male CEOs.

Based on the discussion above, we expect that male analysts' questions and female analysts' questions differ in their likelihood of being followed with further questions, having a preface statement, lacking self- or other-references, and beginning with negative formulations such as *isn't it* or *aren't you*, all of which are consistent with verbal aggressiveness. Hypothesis one is stated in the null form because either a positive or a negative association is plausible. In contrast, we expect male analysts to be more verbally aggressive when the CEO is female, consistent with an out-of-group bias. Thus, hypothesis two has a directional prediction because we lack relevant theory for male analysts being more verbally aggressive to male CEOs. In summary, we hypothesize that:

H1: Questions by male and female analysts do not differ in their levels of verbal aggressiveness.

H2: Questions by male analysts are more verbally aggressive when the CEO is female.

[14] Interruptions by analysts are difficult to study in the context of conference calls, which, being moderated, limit analysts' ability to interrupt. Hence, we do not include interruptions in our empirical analysis.

IV METHODS

Processing of earnings conference call transcripts and transcript data

To analyze earnings conference call transcripts, we use a self-written java program. The program utilizes all available transcripts of quarterly conference calls downloaded in a txt-file format from the LexisNexis database. The process involves several steps. First, we extract header information with the general characteristics of each transcript from the text file (e.g., name of the company, date and firm-year quarter of the earnings conference call, total length of the call). We then identify individual participants (generally, each participant is in a new paragraph and their name is in capital letters, followed by their role and firm) and based on the provided role descriptions, classify them as either CEOs[15] or analysts.[16] We also separate the management discussion and the Q&A parts of the call. We define the management discussion as the text segment that ends when the first analyst speaks. Lastly, we measure verbal aggressiveness and other linguistic characteristics (e.g., number of words spoken) for each participant separately for each call.

Data

We start with 539,801 analyst-firm-quarter observations for which we have transcripts of quarterly conference calls from LexisNexis (Fair Disclosure Wire) from 2005–2018 and firm-level control variables from Compustat, CRSP, and I/B/E/S. We drop 816 (994) observations because we are unable to unambiguously assign the gender of the analyst (CEO) and 393,490 observations because we cannot merge these observations with analysts' individual forecast data from I/B/E/S (e.g., these participants are buy-side analysts, journalists, short sellers, and sell-side analysts from

[15] Participants coded as CEOs have "CEO" or "Chief Executive Officer" in their role description.
[16] At this point, we do not attempt to distinguish between buy-side and sell-side analysts. Later, we restrict our sample to analysts with individual I/B/E/S forecasts, leaving us with a sample of sell-side analysts only.

brokerage firms not/no longer covered by I/B/E/S).[17] This leaves us with 144,501 analyst-firm-quarter observations for 39,209 unique calls. Each year, on average, there are 2,801 calls where we can obtain at least one individual forecast from I/B/E/S (ensuring that our sample consists of only sell-side analysts).[18] This is somewhat less than for comparable studies, a difference that most likely results from the use of different databases for conference call transcripts.[19] We have, on average, 3.685 (median: 6.00) unique sell-side analysts per call in our final sample, where we were able to identify their likely gender. This is reasonably comparable with prior studies. For instance, Call et al. (2021) identify 6.169 sell-side analysts per call, on average, in their sample (including analysts without available I/B/E/S data). Table 1 presents our sample selection process.

We correct for a potentially endogenous selection of CEOs with the inverse Mills' ratio utilizing two gender-related exclusion restrictions. We obtain yearly data for the male (female) share of workers per industry from the Labor Force Statistics in the current population survey (Files 17 and 18 of the survey)[20] and per US county from the American Community Survey Employment Status, available via the U.S. Census Bureau.[21] We link county-level data to a firm's

[17] In 2018, 88 unique brokerage firms stopped providing non-anonymous individual forecasts via I/B/E/S (both currently and retrospectively). These firms included larger brokerage houses such as Bank of America Merrill Lynch, Barclays, Morgan Stanley, and RBC Capital Markets (as communicated in the Thomson Reuters product change notification of September 12, 2018; available via WRDS). We identify 331,031 analyst-firm-quarter observations in our initial conference call sample that we cannot match with individual I/B/E/S analyst forecasts as I/B/E/S (no longer) provides non-anonymous individual forecasts for these analysts. Comparing the gender distribution and the (gender-related) verbal aggressiveness of these analysts with our main sample, we observe similar patterns. Female sell-side analysts are 12.4 percent of the non-matched sample of sell-side analysts (compared to 11.6 percent in our main sample). The average verbal aggressiveness score for the non-matched sell-side analysts is slightly lower (1.940 vs 2.013) than in our main sample. In the non-matched sample, we observe male analysts to be more verbally aggressive than female analysts. The magnitude is similar to that in our main sample (an average of 1.962 for male analysts (main sample: 2.026) vs. 1.840 for female analysts (main sample: 1.956) in the non-matched sample).

[18] We focus on sell-side analysts because they ask more questions during conference calls and because buy- and sell-side analysts differ in their incentives and behavior (Jung, Wong, and Zhang 2018; Call, Sharp, and Shohfi 2021).

[19] For instance, Jung et al. (2018) use Thomson Reuters StreetEvents transcripts and derive 5,798 call transcripts per year. We observe similar univariate characteristics for our firm- and analyst-level control variables, suggesting that the samples across different conference call transcript data providers do not differ systematically.

[20] Available on the website of the U.S. Bureau of Labor Statistics via https://www.bls.gov/cps/tables.htm#annual as part of the Labor Force Statistics from the Current Population Survey.

[21] Data is available within TableID: DP03 of the American Community Survey (ACS) via https://data.census.gov/cedsci/all?d=ACS%201-Year%20Estimates%20Data%20Profiles.

headquarter address using address data from Compustat. We translate a firm's address to GPS coordinates using Google Maps Geocoding API, then assign those GPS coordinates to counties based on shapefiles from the Census Bureau's MAF/TIGER geographic database.

As the gender of analysts and CEOs is not identified in conference call transcripts, we obtain it using the gender estimation tool provided by Gender API (gender-api.com). To estimate the gender, Gender API utilizes data from publicly available governmental sources and enriches them with data crawled from social networks. Gender API comprises almost 2,000,000 names and has been widely used by prior researchers to estimate gender (Caplar et al. 2017).[22]

Model development

To test our two hypotheses, we employ a linear regression model. Our model has an analyst-firm-quarter panel structure; that is, each analyst that participates in a firm's conference call is a unique observation, and their aggressiveness is the dependent variable. To test hypothesis one, we include, in model (1), a dummy variable for the gender of the analyst (*MALEANALYST*). We briefly introduce all control variables here and provide detailed definitions in appendix 1. We control for firm-level factors that have been identified as determinants of tone in the literature (e.g., Huang et al. 2014). Specifically, we control for analysts' consensus future expectation (*AF*), analysts' consensus forecast error (*AFE*), business segment (*BUSSEG*), geographical segment (*GEOSEG*), earnings (*EARN*), change in earnings (*DELTAEARN*), a loss indicator (*LOSS*), market value (*MV*), Tobin's Q (*Q*), stock market return (*RET*), sales growth (*SALESGROWTH*), firm size (*SIZE*), earnings volatility (*STDEARN*), and return volatility (*TOTRISK*).

[22] Prior studies such as Milian et al. (2017) have used the gender.c open-source file, which contains 45,836 first names. Yet 9,658 of these first names are ambiguous in terms of the assigned gender, and a significant number are not included in the open-source file. Therefore, we use a commercial service provider, Gender API, as this allows us to identify the gender for almost all of the analysts and CEOs (99.66 percent).

As the CEO's management discussion part of the conference call could impact the analysts' questions, we control for the length of the CEO's speech (*CEOLENGTH*) as well as the CEO's positive (*CEOPOSITIVE*) and negative tone (*CEONEGATIVE*) (Brockman et al. 2015). We also control for analyst-level variables that could drive their questioning (Milian et al. 2017). Specifically, we control for their past status (*AWARDBEFORE*) and current status as a top-three, star analyst (*STARANALYST*) (Corwin and Schultz 2005; Liu and Ritter 2011), relative individual accuracy (*ACCURACY*), firm experience (*FIRMEXPERIENCE*), general experience (*GENERALEXPERIENCE*),[23] how busy they were in a quarter (*NUMBERCALLS*), whether they cover firms in multiple industries (*ANALYSTMULTIND*), the size of the brokerage firm they work for in a quarter (*BROKERSIZE*), the prestige of the brokerage firm they work for in a quarter (*BROKERAWARDS*), and the number of analysts participating in the call (*NUMBERANALYSTSCALL*). Lastly, we use analysts' participation on the firm's prior calls (*PREVIOUSPART*) as a proxy for the analyst-management relationship (Milian et al. 2017).

The dependent variable *AGGRESSIVENESS* is proxied for by either *DIRECTNESS*, *FOLLOWUP*, *NEGATIVEQ*, or *PREFACE*. We also use a composite score of all four aggressiveness measures (*AGGRSCORE*), where the value ranges from zero to four. In addition, some studies (e.g., Huang et al. 2014) differentiate between normal and abnormal tone. To capture abnormally high verbal aggressiveness, we include *HIGHAGGR*, a binary variable indicating whether an analyst uses two or more types of verbal aggressiveness within the same call. Higher values imply more verbal aggressiveness for all four individual measures as well as for the composite and the

[23] As these variables are calculated based on the earnings conference call transcript data, the variable is truncated at the year 2005. We acknowledge that this might underestimate analysts' conference call experience if they participated in conference calls before 2005. However, earnings conference calls were rather uncommon before 2005, so we believe this to be a rather minor issue. To ensure this caveat does not affect our main results, we alternatively measure analyst experience using the initial individual analyst forecast using data from I/B/E/S. Our results hold.

abnormally high verbal aggressiveness measures. Consequently, positive (negative) coefficients for male analysts (*MALEANALYST*) would imply that male analysts are more (less) verbally aggressive than female analysts are. All aggressiveness measures are estimated for each analyst *a* participating in a conference call for firm *i* in year-quarter *t*. Finally, we cluster standard errors at the firm-level[24] and include Fama-French 48 industry fixed effects as well as year-quarter fixed effects to control for unobservables at the year-quarter and industry level.[25] The empirical model is set up as follows (with X being a vector of controls and ϵ being the error term):

$$AGGRESSIVENESS_{\mathrm{a,i,t}} = ß_0 + ß_1 \mathrm{MALEANALYST}_{\mathrm{a,I,t}} + X_{a,i,t} + \mathrm{INDUSTRY\ FE} + \mathrm{YEAR\text{-}QUARTER\ FE} + \varepsilon_{a,i,t.} \quad (1)$$

For hypothesis two, we want to test whether male analysts are more verbally aggressive when they question female CEOs. Therefore, we include a dummy variable for the gender of the CEO (*MALECEO*) and use an interaction term between *MALEANALYST* and *MALECEO* to estimate coefficients for the male analyst–female CEO dyad. With this two-way interaction term and its stand-alone terms, we can hold constant the difference between male and female analysts and focus on the male analyst–female CEO dyad. We expect less verbally aggressive questions from male analysts if the CEO is male and, consequently, a larger difference between male and female analysts after controlling for CEO gender.

[24] We cluster standard errors at the firm-level as analyst questioning behavior is likely to be clustered within firms rather than across firms (e.g., a similar set of analysts that participates in conference calls of a firm over time).
[25] Nevertheless, to ensure our results are not sensitive to the fixed effects structure employed, we rerun our main models replacing industry and year fixed effects with conference call fixed effects. For tests of H1, we continue to find positive and significant coefficients for all six different aggressiveness variables. Specifically, the coefficient of *MALEANALYST* is positive and significant at the 1 percent level for *DIRECTNESS*, *FOLLOWUP*, *PREFACE*, *AGGRSCORE*, and *HIGHAGGR*, as well as positive and significant at the 10 percent level for *NEGATIVEQ*. For tests of H2, the interaction term *MALEANALYST * MALECEO* remains significantly negative at the 1 percent level for *FOLLOWUP*, and significantly negative at the 10 percent level for *DIRECTNESS*, *AGGRSCORE*, and *HIGHAGGR*.

Univariate statistics

Table 2 presents univariate statistics. The gender distribution is quite uneven for both CEOs and analysts. Female CEOs are much less common than male CEOs (7.5 percent of the sample CEOs are women). This is in line with Catalyst (2018), who finds that although 47.7 percent of Fortune 500 firms' employees are female, only 5.2 percent of these firms have a female CEO. Similarly, only 11.6 percent of the analysts in our sample are female (*MALEANALYST* mean: 0.884).[26] This too is in line with prior studies. For instance, female analysts account for 9 percent of the sample in Milian et al. (2017). Finally, we find that female sell-side analysts are not evenly distributed across industries but are concentrated in specific industries.[27]

The distribution of verbal aggressiveness measures shows a considerable degree of heterogeneity across analysts. In general, analysts use aggressiveness measures quite frequently: 37.6 percent use direct questions *(DIRECTNESS)*, 70.4 percent use follow-up questions (*FOLLOWUP*), 14.5 percent use negative questions (*NEGATIVEQ*), and 78.8 percent preface their statements (*PREFACE*). As the aggressiveness measures are all defined as indicator variables, the standard deviations of all four measures signal considerable differences across analysts' questioning behavior (std. dev.: *DIRECTNESS*: 0.484, *FOLLOWUP*: 0.457, *NEGATIVEQ*: 0.352, *PREFACE*: 0.409). Overall, each analyst within each call uses approximately two out of the four types of verbal aggressiveness (*AGGRSCORE* mean: 2.013). In comparison, the positive and negative words that are used to determine linguistic tone – the focus of prior research – are relatively uncommon.[28] Linguistic differences also show up when we look at CEOs. On average, a CEO speaks

[26] The share of female analysts is relatively stable over time (without a time trend) and ranges between 8.58-12.76 percent depending on the year.
[27] We find the highest share of female analysts in the consumer nondurables sector (19.30 percent female), followed by the wholesale, retail, and some services sector (14.59 percent) and the telephone and television transmission sector (14.12 percent). The lowest female analyst share is in the business equipment sector (6.22 percent).
[28] In untabulated analysis, we find 4.456 positive and 1.596 negative words for every 100 words spoken by analysts.

1,199 words (exp(7.089)=1,199) with the 25th and 75th percentiles spanning 862 to 1,760 words. Again, we find that CEOs use positive words (*CEOPOSITIVE*) more often than negative words (*CEONEGATIVE*). All of the other variables are also in line with the findings in previous literature (Srinidhi, Gul, and Tsui 2011; Huang et al. 2014).

We present Pearson correlations for all variables in Table 3. These correlations suggest significant ($p<0.01$) gender differences in the aggressiveness of analysts' questions. Male analysts are more direct (*DIRECTNESS*), ask more follow-up questions (*FOLLOWUP*), ask more negative questions (*NEGATIVEQ*), and use more preface statements (*PREFACE*) than female analysts. Gender differences also seem to exist for CEOs. During the management discussion section of the conference call, male CEOs (*MALECEO*) give shorter talks (*CEOLENGTH*) and use more negative words (*CEONEGATIVE*) and less positive (*CEOPOSITIVE*) words. The Pearson correlations also suggest that analysts use different combinations of the aggressiveness measures (the highest correlation being between *FOLLOWUP* and *PREFACE* with coef.: 0.203) and that these measures can substitute for one another. For instance, the correlations between *DIRECTNESS* and *FOLLOWUP* (coef.: -0.142) and between *PREFACE* and *DIRECTNESS* (coef.: -0.033) are both significantly negative. Lastly, the correlations also indicate that more experienced analysts (*FIRMEXPERIENCE* as well as *GENERALEXPERIENCE*) and busier analysts (*NUMBERCALLS*) are verbally more aggressive, as three out of four correlations are significantly positive.

Table 4 documents mean differences in verbal aggressiveness across genders. Univariate t-tests for non-zero differences between male and female analysts consistently show differences between male and female analysts' verbal aggressiveness, which is in line with hypothesis one. In comparison to female analysts, male analysts use direct questions (*DIRECTNESS*) 2.64 percentage points more often, follow-up questions (*FOLLOWUP*) 4.27 percentage points more often, and negative questions (*NEGATIVEQ*) 0.92 percentage points more often, and they preface (*PREFACE*) their questions 3.20 percentage points more often. Our composite measure shows a difference of 0.11 points more in aggregate. Lastly, male analysts are 4.99 percentage points more likely to be (abnormally) highly verbally aggressive (*HIGHAGGR*), relative to female analysts.

V RESULTS

Main results

To investigate whether the univariate differences hold after controlling for firm- and analyst-level factors, we perform multivariate tests. First, we test whether male analysts and female analysts exhibit different levels of verbal aggressiveness, consistent with hypothesis one. We report our results in Table 5. Columns (1) to (6) of Table 5 show multivariate regression results using different measures of verbal aggressiveness as the dependent variable. In all six regressions, the adjusted R-squared is low (depending on the specification, between 1.4 percent and 8.2 percent) but comparable to that in prior studies investigating the determinants of tone (e.g., Milian et al. 2017). As expected, we find considerable differences between male and female analysts. Male analysts are more direct than female analysts (*DIRECTNESS*: 0.026, p-value: 0.000), ask more follow-up questions (*FOLLOWUP*: 0.036, p-value: 0.000), ask more negative questions (*NEGATIVEQ*: 0.009, p-value: 0.008), and use more prefaces before questions (*PREFACE*: 0.028, p-value: 0.000). Given these results, it is not surprising that the composite measure is also positive and significant (*AGGRSCORE*: 0.100, p-value: 0.000), as is the abnormally high aggressiveness measure (*HIGHAGGR*: 0.044, p-value: 0.000).

These coefficients are fairly large and appear to be economically meaningful. These results indicate that for male analysts, direct questions are 2.6 percentage points higher, follow-up questions are 3.6 percentage points higher, negative questions are 0.9 percentage points higher, and preface statements are 2.8 percentage points higher than for female analysts. Overall, our findings are consistent with men being more verbally aggressive than women and suggest that self-selection by female analysts (Kumar 2010) does not translate into higher verbal aggressiveness on their part. The coefficients on the control variables vary somewhat across the six regressions, but the number of business segments, CEO speech length, and analysts' busyness seem to be important to control for. In addition, in five of six regressions, the coefficients of *STARANALYST* and *PREVIOUSPART* are significantly positive, suggesting that analysts with more prestige (*STARANALYST*) and a closer relationship to management (*PREVIOUSPART*) are more likely to be verbally aggressive.

Second, we investigate whether male analysts are more verbally aggressive when the CEO is female (hypothesis two). These results are reported in Table 6. The overall fit of the model is comparable to the results reported in Table 5 for all six specifications. In addition, the coefficients of most of the control variables are similar to those in the results obtained before. In these regressions, we are interested in two coefficients. The *MALEANAYST* standalone coefficient compares male and female analysts when they question a female CEO (female analysts asking questions of female CEOs are the reference group). For five of the six regressions, the coefficients are statistically significant and considerably larger than in Table 5. Specifically, when the CEO is female, a male analyst uses 5.3 percentage points (vs. 2.6 percentage points without considering CEO gender) more direct questions, 9.5 percentage points (vs. 3.6 percentage points) more follow-up questions, and 3.4 percentage points (vs. 2.8 percentage points) more preface statements. The coefficient for negative questions is insignificant.

The interaction between *MALEANALYST**MALECEO* picks up the difference in verbal aggressiveness when male analysts ask questions of male CEOs (vs. female CEOs). A negative interaction term would indicate an out-of-group bias for the male analyst–female CEO dyad. Based on the coefficients for *MALEANALYST*MALECEO*, it appears that verbal aggression by male analysts is somewhat more pronounced when the CEO is female. The coefficients are statistically significant and have a meaningful effect size in four of the six regressions (*NEGATIVEQ* and *PREFACE* are statistically insignificant). When male analysts question female CEOs, they use 2.4 percentage points more direct questions (*DIRECTNESS*: -0.024; p-value: 0.069) and 6.5 percentage points more follow-up questions (*FOLLOWUP*: -0.065; p-value: 0.010) than when they question male CEOs. For the composite measures, we find considerable differences as well. The aggregate score is 0.79 points lower (*AGGRSCORE*: -0.079; p-value: 0.039) and the abnormally high aggressiveness measure is 2.7 percentage points lower (*HIGHAGGR*: -0.027; p-value: 0.090).[29] Interestingly, female analysts do not differ in their verbal aggressiveness towards female vs. male CEOs. The coefficient *MALECEO* tests for a female analyst asking a female vs. male CEO. Except for *FOLLOWUP* (which is significant and positive; so female analysts do ask more follow-up questions to male vs. female CEOs), all coefficients are insignificant suggesting that female analysts do not exhibit an out-of-group bias to a larger extent.

Looking at the total effect (e.g., the sum of the coefficients of all interaction term elements, which are *MALEANALYST*, *MALECEO*, and *MALEANALYST * MALECEO*), we can compare the two same-gender groups. The sum of the coefficients of all constituting elements of the interaction terms (both stand-alone terms and the interaction term itself) represents the marginal effect of a male analyst asking a male CEO compared to the base group, which is a female analyst (*MALEANALYST*=0) asking a female CEO (*MALECEO*=0). We find that the male dyad is linked to more

[29] To better understand whether male analysts are also more aggressive to male CEOs than female analysts (but perhaps to a lesser extent than to female CEOs), we rerun our analysis with a subsample of male CEOs only. We continue to find significant differences between male and female analysts, yet with smaller differences for all verbal aggressiveness measures compared to the full sample. For instance, male analysts ask 2.8 percentage points more follow-up questions (*FOLLOWUP*: 0.028; p-value: 0.000) than female analysts (compared to 3.6 percentage points when we include observations with female CEOs).

verbally aggressive questions for all four individual and both composite measures, relative to the female dyad. Specifically, we find that the male dyad for directness is 4 percentage points larger (0.053+0.011-0.024=0.04) than the female dyad. For follow-up questions (negative questions, preface statements), the difference equals 9.7 percentage points (1.2 percentage points, 3.4 percentage points), and for the composite measures *AGGRSCORE* and *HIGHAGGR* the male dyad is 0.163 points and 6.9 percentage points larger, respectively, than the female dyad.

Overall, we find that male analysts are more verbally aggressive to female CEOs, particularly in terms of directness and follow-up questions. We argue that these are economically significant differences that have not been detected by prior research. Our finding of an out-of-group bias in male analysts' verbal aggressiveness towards female CEOs complements Jannati et al. (2020), who find that male analysts forecast lower earnings for firms headed by female CEOs.

Controlling for endogenous selection

Considerable research has shown gender differences in the context of executives and directors (e.g., Barua et al. 2010; Srinidhi et al. 2011; Francis et al. 2013; Francis et al. 2014; Francis, Hasan, Park, and Wu 2015). In particular, females are less likely to be selected as CEOs even when their skills are comparable to their male counterparts (Srinidhi et al. 2011). Therefore, CEO selection and gender are likely to be endogenous.[30] We control for this potential non-random selection of CEOs based on unobservables (Lennox, Francis, and Wang 2012) with the commonly employed Heckman (1979) inverse Mills' ratio approach using a probit model. We include Fama-

[30] On the contrary, the selection of analysts to firms is based primarily on industries and is rather sticky across time (Francis 1997; McNichols and O'Brien 1997). Yet, men and women cover firms with different firm characteristics. In untabulated analyses, we test whether firm characteristics differ within industry for male vs. female analysts. For this purpose, we demean firm size, stock market returns, and profitability by industry-year-quarter and perform t-tests for mean differences between firms covered by male and firms covered by female analysts. We find that female analysts cover primarily smaller firms as well as firms with lower stock returns and lower earnings (all differences significant at $p<0.01$). This highlights the importance of controlling for firm characteristics in our main analysis.

French 48 industry and year fixed effects to implicitly control for unobservable factors that are constant within these groups. In the first step, we proxy for the determinants of the probability that a man (woman) is the CEO of firm *i* in year *t*. For our two exclusion restrictions, we use the share of male employees in an industry per year, and the share of male employees in a county per year (Knyazeva, Knyazeva, and Masulis 2013). We believe each fulfills the criteria for valid exclusion restrictions: relevance for the selection in the first stage, and no direct impact on our dependent variable in the second stage.

Women are more likely to be promoted to CEO when a firm performs poorly (Ryan and Haslam 2005). We therefore control for a firm's current and expected future performance with the previous quarter's stock market return, earnings before extraordinary items, change in earnings, and analyst consensus one-quarter-ahead forecast. As larger firms (firms with stronger corporate governance) are more likely to face greater external (internal) pressure to comply with societal expectations such as gender diversity (Demsetz and Lehn 1985), we also control for a firm's size, Tobin's Q, and corporate governance strength (using the KLD strength score).

In the second-stage model, we use the inverse Mills' ratio as the lambda selection coefficient to make sure that linguistic differences towards female and male CEOs are not driven by the endogenous selection of female/male CEOs, as men (women) are more likely to be promoted to CEO at a well- (poorly) performing firm. All control variables are as defined for the main model (see Appendix 1). We also control, in the second stage, for unobservables at the industry level and time level with Fama-French 48 industries and year-quarter fixed effects, respectively.

In our first-stage model results (Table 7, Panel A), *MALESHAREINDUSTRY* as an exclusion restriction is positively associated with the likelihood that a CEO is male, whereas the coefficient for *MALESHARECOUNTY* is insignificant. Next, we include the inverse Mills' ratio in the second-stage. We find negative and significant coefficients for the inverse Mills' ratio for all verbal aggressiveness measures (p-values range from 0.000 to 0.013), suggesting that unobservables linked to the gender-related CEO selection are negatively and significantly associated with the observable verbal aggressiveness behavior of analysts (i.e., a negative selection bias). However, even after correcting for potentially endogenous CEO selection linked to unobservables, we continue to find negative interaction terms for *MALEANALYST* * *MALECEO* with similar effect sizes and significances to the main results (Table 7, Panel B). Overall, our earlier results do not appear to be driven by the endogenous selection of the CEOs.

Star analysts

Next, we turn to the question of whether there is an association between the verbal aggressiveness of female analysts and their achieving All-American analyst status. Inclusion on the All-American analyst list creates visibility and respect for analysts and is associated with substantial financial rewards – in effect, it makes them star analysts (Beunza and Stark 2004; Groysberg, Lee, and Nanda 2008; Giorgi and Weber 2015). Whether such an association exists is ex-ante unclear. On the one hand, sell-side analysts who are more verbally aggressive may be more credible to the buy-side analysts who vote for the award. Verbally aggressive questioning is consistent with analysts adopting more of a monitoring role at the potential cost of straining their relationships with management. There is evidence of similar behavior in presidential press conferences where Clayman and Heritage (2002) attribute increasing levels of verbal aggressiveness to journalists presenting themselves as independent agents seeking to hold a powerful individual accountable (whom they depend on for access). Moving to earnings conference calls, Brown et al. (2015) provide survey evidence that analysts are willing to risk their relationship with firm management to issue below-consensus forecasts and recommendations that are more credible to their investing clients.

Thus, analysts may also be willing to trade-off increasing their credibility with investors at the potential harm to their relationships with managers by asking verbally aggressive questions. Female analysts may be particularly willing to do so because of self-selection into a male-dominated profession and the "Avis syndrome."

On the other hand, given that women are in general more polite (Hartman 1976), more likely to hedge when asking questions (Crosby and Nyquist 1977), and more likely to use disclaimers (Lakoff 1975), verbal aggressiveness may be seen as more of a negative for women than for men. Buy-side analysts, most of whom are male (as are most sell-side analysts), may be uncomfortable with such aggressiveness and may vote against the verbally aggressive female sell-side analysts. This type of pattern would be consistent with research showing that women are punished for violating gender norms (Rudman 1998; Heilman and Okimoto 2007; Egan, Matvos, and Seru 2022). In this case, we would expect negative coefficients for our verbal aggressiveness measures for female analysts after controlling for forecast accuracy.

To test our predictions, we regress whether an analyst received an AA award (*STARANALYST*) on our verbal aggressiveness measures. Following Corwin and Schultz (2005) as well as Liu and Ritter (2011), we classify analysts as stars if they are ranked in the top three by *Institutional Investor*.[31] We obtain the voting data directly from *Institutional Investor* to avoid errors arising from hand-collecting/coding the lists from past *Institutional Investor* issues. For our sample period, the *Institutional Investor* dataset includes 568 unique analysts who were ranked in the top three at least once. We fuzzy match these analysts based on their first name, last name, and brokerage firm

[31] We do not consider runners-up, for two reasons. First, the number of runner-up places differs across industries and years. While in some industries/years no runner-up status is awarded at all, in others ten or more analysts are listed as runners-up (e.g., Biotechnology/Mid- & Small-Cap 2017). Second, the career benefits should be particularly strong for analysts in the top three, as they receive significant media attention. For instance, the *Wall Street Journal* traditionally interviews only the top three analysts and publishes the interviews together with brief sketches of each analyst and their latest stock picks.

with our main sample, and manually verify the fuzzy matches afterward. We were able to match 360 of the 568 star analysts to our main sample.[32] Of these 360 analysts, 13.5 percent are female and 86.5 percent are male (compared to 11.6 percent and 88.4 percent for the main sample), which is in line with prior studies' findings that female analysts are more likely to become star analysts (Green et al. 2009; Li et al. 2013). As analysts usually participate in the conference calls of multiple firms, we collapse our sample to one observation per analyst-year and take the mean values of all verbal aggressiveness and control variables (Hilary, and Hsu 2013) to have the same structure as our dependent variable (the *Institutional Investor* list is published annually). To ensure that we pick up the effect that is specifically attributable to verbal aggressiveness, we include all analyst- and broker-level control variables from our main model and additionally control for analysts' use of negative, positive, and praise words (*ANALYSTNEGATIVE*, *ANALYSTPOSITIVE*, *ANALYSTPRAISE*). We present these results in Table 8.

Regardless of whether we include all verbal aggressiveness measures separately (column (1)) or in aggregate using *AGGRSCORE* (column (2)) and *HIGHAGGR* (column (3)), we consistently find that female analysts who ask verbally aggressive questions have a higher likelihood of becoming star analysts. We find positive and significant coefficients for *DIRECTNESS*, *FOLLOWUP*, *NEGATIVEQ*, *AGGRSCORE*, and *HIGHAGGR* (only *PREFACE* is insignificant), with economically meaningful effect sizes. For instance, for *FOLLOWUP* the effect size equals 9 percent (calculated as 1/(1+exp(2.289))=0.09). However, we find no significant association for male analysts who ask verbally aggressive questions, as the positive significant standalone terms for the

[32] We went through all non-matches (i.e., star analysts who are not matched to our sample). The vast majority of non-matches belong to analysts working for large and well-known brokerage firms that are not/no longer covered by I/B/E/S (see footnote 17).

verbal aggressiveness measures are offset by the negative and significant interaction terms (*MALEANALYST * AGGRESSIVENESS*).[33] For the control variables, we find that the visibility of analysts (*NUMBERCALLS*), the reputation of the brokerage firm (*BROKERAWARDS*), and having previously received an award (*AWARDBEFORE*) are all significant positively associated with the likelihood of becoming a star analyst.

Next, we investigate whether the association between verbal aggressiveness and the likelihood of males and females becoming star analysts differs across industries with high and low shares of female analysts. In the three industries with the highest female share (consumer nondurables sector; wholesale, retail, and some services sector; and telephone and television transmission sector), 16.5 percent of all analysts are women, compared to 8.9 percent of analysts in other industries. To test for differences across industries with high vs. low female analyst shares, we triple interact our verbal aggressiveness and gender variables with *HIGHFEMALESHARE* – a dummy variable indicating whether an analyst belongs to an industry with a high female analyst proportion (Fama-French 10 industries 1, 6, and 7) – while omitting industry fixed effects, as they are perfectly colinear with *HIGHFEMALESHARE*.[34] We present the results in column (4).

We continue to find significant positive coefficients for the stand-alone verbal aggressiveness measures and negative coefficients for the interaction terms *MALEANALYST * AGGRESSIVENESS*. However, none of the four triple-interacted terms with *HIGHFEMALESHARE* is significant, suggesting that the association between analysts' gender, use of verbal aggressiveness, and likelihood of becoming a star analyst is robust to the gender distribution across industries.

[33] We run joint F tests of the sum of each verbal aggression measure's coefficients plus the corresponding interaction term's coefficient against the null that the sum of the coefficient equals zero (e.g., *DIRECTNESS + DIRECTNESS * MALEANALYST* =0). The joint F tests are all insignificant.
[34] We also rerun this test with industry fixed effects and find insignificant coefficients for all four triple-interacted terms with *HIGHFEMALESHARE*.

Additional analysis and robustness tests

To increase confidence in our results, we perform additional tests.[35] First, questions with a negative tone could be viewed as "aggressive," so we rerun our tests with negative tone as the dependent variable. We find that male analysts have a more negative tone and that the effect is more pronounced for their questions to female CEOs (similar to our other measures of verbal aggressiveness). To ensure that our other results do not simply pick up negative tone, we rerun our main tests for a subsample of questions that either have a positive or a neutral net tone (i.e., we exclude questions with a negative tone). All our results hold. Thus, it appears that the effect of verbal aggressiveness captures a different dimension of analyst questions than does the proportion of negative words (negative sentiment). We did not include negative tone as a control in our other models, as we do not view it as a determinant of other types of verbal aggressiveness (instead, we view it as a potential substitute). Second, we exclude from our sample the year-quarters belonging to 2008 and 2009 – the period of the financial crisis – as the crisis was an exogenous shock to firm and stock market performance (potentially affecting how analysts ask questions or react to changes in performance); we then rerun our main models. We obtain similar coefficient sizes and significance levels.[36] Third, we exclude financial firms. Our main results hold. Fourth, we rerun our main model with logit instead of OLS regressions[37] and cluster standard errors by analyst instead of by firm. The coefficients for our variables of interest remain similar in statistical significance.

[35] For the sake of brevity, results for these regressions are untabulated and are available upon request.
[36] Only *NEGATIVEQ* is no longer significant at the 1 percent level, but instead at the 5 percent level in the test for H1; all other gender-related coefficients are significant at the same level and with a similar effect size compared to the main results for H1 and H2.
[37] Specifically, all regressions using logit instead of OLS regressions have the same significance levels with one exception: For *PREFACE* in the test for H2, the coefficient *MALEANALYST* is no longer significant at the 5 percent level (but it remains significant at the 10 percent level).

VI CONCLUSION

This paper provides evidence that the verbal aggressiveness of analysts' questions is significantly associated with both the gender of the CEO fielding the question and the gender of the analyst asking the question. First, we find that male analysts' questions are more verbally aggressive than female analysts' questions. Second, we show that this difference is more pronounced when the CEO is female, which is consistent with an out-of-group bias. Finally, we investigate whether verbal aggression is associated with different career consequences for male vs. female analysts. Our findings suggest that female analysts who ask verbally aggressive questions have a higher likelihood of being selected as a top-three analyst on *Institutional Investor's* annual list of best analysts. We fail to find a similar result for male analysts.

Differences in linguistic styles can have real consequences. For example, Dupas et al. (2021) find that women presenters in economics job talks are asked more hostile questions, which, the authors suggest, may be associated with women being underrepresented in the field. In general, differences in male and female linguistic styles have potential implications for who gets credit for work and for judgments of confidence and competence (Tannen 1995). Linguistic styles also affect how men and women are viewed in the power hierarchy (Schmid Mast 2001; Brescoll 2011) and how criticism is perceived (Tracy and Eisenberg 1990). Given these findings, sell-side firms might want to ensure that their managers are aware of the differences between the linguistic styles of men and women (if they are not already doing so). Similarly, differences in male/female linguistic styles could be considered by voters for Institutional Investor's All-American analyst awards.

Appendix 1: Variable definitions

Exogenous Variables		
DIRECTNESS	=	Indicator variable that takes the value of one if an analyst's question lacks a personal reference (self- and other-referencing indicate a lack of verbal aggressiveness) and the value of zero if he/she includes a self- or other-reference in his/her question. A self-reference is when any of the following terms are used: "I wonder"/"I am wondering"/I was wondering"/"I have been wondering"/ "I´d like to ask"/"I would like to ask"/ "Can I ask"/"May I ask" and an other-reference is when any of the following terms are used: "Can you"/"Could you"/"Will you"/"Would you." **Example of an indirect question with a self-reference (Greg Lewin from Lewin Capital at the Q4 2013 Parkervision earnings conference call):** "(…) Can I ask, so you started that by saying you weren't looking for funds. Did they come looking for you or did you come looking for them?".
FOLLOWUP	=	Indicator variable that takes the value of one if an analyst asks a question directly after an executive replies to an earlier question, and zero otherwise. We require the text of the analyst's question to include either "?", or a question-indicating verb such as "wonder*", or "explain*" to ensure that the analyst is not merely acknowledging a reply to an earlier question. **Example of a follow-up question (John Pandtle from Raymond James at the Q1 2006 Alabama National BanCorp earnings conference call):** "(…) I was wondering in Florida if you're still seeing better margins, better deposit pricing than perhaps that you see in Alabama? (…)" (Reply by management) "Okay. And then as a follow-up question in terms of balance sheet management, Will, and thinking about perhaps the eventual end of the Fed tightening cycle, kind of your outlook in terms of timing of that. (…)".
NEGATIVEQ	=	Indicator variable that takes the value of one if any of the questions asked by the analyst includes a negative question, and zero otherwise. A negative question is one where the first word of a sentence ending with a "?" includes "*n't*" such as "Isn't it", "Couldn't you" or "Wouldn't you." **Example of a negative question (Doug Schenkel from Cowen and Company at the Q4 2013 Myriad Genetics earnings conference call):** "(…) Isn't it inevitable that there's going to be conflicting claims made by competitors? And, if, so doesn't this accelerate FDA LDT regulation?".
PREFACE	=	Indicator variable that takes the value of one if the analyst frames his/her question with a statement preceding the question, and zero otherwise. Preface statements occur when there is at least one additional sentence between the welcoming sentence (sentences including words such as "Hello", "Hi", "Hey", "Good Morning", "Good Afternoon" or "Good Evening") and sentences with actual questions (sentences ending with a "?" and/or including question-indicating verbs such as "wonder*" or "explain*"). **Example of a question with a preface (Cosmos Chiu from CIBC World Markets at the Q4 2011 San Gold Corp earnings conference call):** "It sounds like you've gone through a lot of service stockpiles that you had at year-end 2011. I was wondering, the grade that you've been processing, is it sort of what you had been expecting from the stockpiles? (…)".
AGGRSCORE	=	Aggressiveness is calculated as the sum of the four individual verbal aggressiveness measures (DIRECTNESS, FOLLOWUP, NEGATIVEQ, and PREFACE). Consequently, the score ranges from 0 (no verbal aggressiveness measures are used by an analyst) to 4 (all four verbal aggressiveness measures are used by an analyst).
HIGHAGGR	=	Indicator variable that takes the value of one if AGGRSCORE is larger than or equal to 2, and zero otherwise.

Endogenous Variables		
ACCURACY	=	Relative analyst forecast accuracy calculated as in Clement and Tse (2003): maximum absolute forecast error of all analysts following a firm in a year-quarter minus the analyst's individual absolute forecast error, scaled by the difference between the maximum and minimum absolute forecast error of all analysts following a firm in a year-quarter. Consequently, higher values indicate that an analyst is more accurate.
AF	=	Analyst consensus forecast for one-quarter-ahead earnings per share, scaled by the stock price per share at the end of the period.
AFE	=	Analyst forecast error defined as the absolute difference per share between actual earnings and the most recent consensus forecast, scaled by the stock price at the end of the period.
ANALYSTMULTIND	=	Indicator variable that takes the value of one if an analyst participates in calls of firms from multiple Fama-French 48 industries within a year-quarter, and zero otherwise.
AWARDBEFORE	=	Number of awards (top 3, star analyst) won by an analyst in previous years scaled by the number of years since the analyst is in the sample.
BROKERAWARDS	=	Natural logarithm of the sum of all awards won by analysts working for a brokerage firm plus one.
BROKERSIZE	=	Natural logarithm of the total number of analyst participants from a brokerage firm within a year-quarter plus one.
BUSSEG	=	Diversification across business segments defined as the natural logarithm of the number of reported business segments plus one. If the item is missing in Compustat, we assign the value of one (before taking the natural logarithm).
CEOLENGTH	=	Total number of words spoken by a CEO during the management discussion part of the earnings conference call.
CEONEGATIVE	=	Share of negative words to total words spoken by a CEO in the management discussion part of an earnings conference call. Negative words are taken from the Loughran and McDonald (2011) negative words list.
CEOPOSITIVE	=	Share of positive words to total words spoken by a CEO in the management discussion part of an earnings conference call. Positive words are taken from the Loughran and McDonald (2011) positive words list.
DELTAEARN	=	Change in earnings before extraordinary items, scaled by lagged total assets.
EARN	=	Earnings before extraordinary items, scaled by lagged total assets.
FIRMEXPERIENCE	=	Natural logarithm of the difference between the current year-quarter and the first quarter the analyst has been in an earnings conference call of the same firm plus one.
GENERALEXPERI-ENCE	=	Natural logarithm of the difference between the current year-quarter and the first quarter the analyst has been in an earnings conference call (any sample firm) plus one.
GEOSEG	=	Diversification across geographic segments defined as the natural logarithm of the number of reported geographic segments plus one. If the item is missing in Compustat, we assign the value of one (before taking the natural logarithm).
LOSS	=	Indicator variable that takes the value of one if EARN is negative, and zero otherwise.
MALEANALYST	=	Indicator variable that equals one if the analyst is male, and zero otherwise.
MALECEO	=	Indicator variable that equals one if the CEO is male, and zero otherwise.
MV	=	Natural logarithm of the market value of equity at the end of the period.
NUMBERANALYSTS	=	Natural logarithm of the number of all participants (not restricted to sell-side analysts) in a call plus one.
NUMBERCALLS	=	Natural logarithm of the number of calls an analyst participates in during a year-quarter plus one.
PREVIOUSPART	=	Number of calls an analyst has been participating in during the last four quarters of the specific firm the call belongs to.
Q	=	Tobin's Q is defined as the book value of total assets minus the book value of equity, plus the market value of equity, scaled by the book value of total assets.
RET	=	Stock return over the current quarter.
SALESGROWTH	=	Average percentage change in sales over the three preceding quarters.
SIZE	=	Firm size measured as the natural logarithm of lagged total assets.
STARANALYST	=	Indicator variable that takes the value of one if an analyst is part of the Institutional Investor's list of the top 3 best analysts in a year (star analyst), and zero otherwise.
STDEARN	=	Standard deviation of EARN calculated over the five most recent quarters, with at least three quarters of data required.
TOTRISK	=	Standard deviation of daily returns during the current period standardized to a mean of zero and a standard deviation of one.
This table defines all variables used in the main models. All continuous variables are winsorized at the 1st and 99th percentiles.		

Table 1: Sample selection procedure

		Analyst-firm-quarter observations	
		Reduction	Observations
(1)	Analyst-transcript observations with available firm-level data controls from Compustat, CRSP, and I/B/E/S		539,801
(2)	Observations with unknown/ambiguous gender of analysts	816	538,985
(3)	Observations with unknown/ambiguous gender of CEOs	994	537,991
(4)	Observations without individual forecast data available in I/B/E/S (i.e., buy-side analysts; journalists; short sellers; sell-side analysts from brokerage firms not covered by I/B/E/S)	393,490	144,501
(5)	**Main model (public U.S. firms, 2005-2018)**		**144,501**

Table 2: Descriptive statistics of regression variables

Variable	N	Mean	S. Dev.	Min	25%	50%	75%	Max
DIRECTNESS	144,501	0.376	0.484	0.000	0.000	0.000	1.000	1.000
FOLLOWUP	144,501	0.704	0.457	0.000	0.000	1.000	1.000	1.000
NEGATIVEQ	144,501	0.145	0.352	0.000	0.000	0.000	0.000	1.000
PREFACE	144,501	0.788	0.409	0.000	1.000	1.000	1.000	1.000
AGGRSCORE	144,501	2.013	0.883	0.000	1.000	2.000	3.000	4.000
HIGHAGGR	144,501	0.745	0.436	0.000	0.000	1.000	1.000	1.000
MALEANALYST	144,501	0.884	0.321	0.000	1.000	1.000	1.000	1.000
MALECEO	144,501	0.920	0.271	0.000	1.000	1.000	1.000	1.000
ACCURACY	144,501	0.514	0.437	0.000	0.000	0.500	1.000	1.000
AF	144,501	0.010	0.018	-0.114	0.006	0.012	0.018	0.060
AFE	144,501	-0.001	0.008	-0.038	-0.002	-0.001	0.000	0.067
ANALYSTMULTIND	144,501	0.964	0.186	0.000	1.000	1.000	1.000	1.000
AWARDBEFORE	144,501	0.071	0.257	0.000	0.000	0.000	0.000	1.000
BROKERAWARDS (ln)	144,501	1.318	1.919	0.000	0.000	0.000	2.303	6.333
BROKERAWARDS (unlogged)	144,501	42.982	114.62	1.000	1.000	1.000	10.000	563.00
BROKERSIZE	144,501	4.327	1.463	0.693	3.434	4.500	5.481	6.987
BUSSEG	144,501	1.099	0.423	0.693	0.693	1.000	1.386	2.079
CEOLENGTH	144,501	7.089	0.550	5.371	6.759	7.135	7.473	8.302
CEONEGATIVE	144,501	0.945	0.574	0.000	0.527	0.830	1.241	2.848
CEOPOSITIVE	144,501	2.498	0.905	0.613	1.844	2.439	3.074	4.984
DELTAEARN	144,501	0.000	0.027	-0.128	-0.005	0.000	0.006	0.139
EARN	144,501	0.008	0.034	-0.197	0.002	0.011	0.022	0.093
FIRMEXPERIENCE (ln)	144,501	2.013	1.146	0.000	1.099	2.197	2.944	4.159
FIRMEXPERIENCE (unlogged)	144,501	12.647	11.616	1.000	3.000	9.000	19.000	64.000
GENERALEXPERIENCE (ln)	144,501	3.051	0.875	0.000	2.708	3.258	3.638	4.159
GENERALEXPERIENCE (unlogged)	144,501	27.187	14.868	1.000	15.000	26.000	38.000	64.000
GEOSEG	144,501	1.255	0.457	0.693	1.000	1.099	1.609	2.565
LOSS	144,501	0.209	0.407	0.000	0.000	0.000	0.000	1.000
MV	144,501	21.466	1.498	17.294	20.400	21.394	22.431	25.616
NUMBERANALYSTS (ln)	144,501	2.308	0.418	1.099	2.079	2.303	2.565	3.219
NUMBERANALYSTS (unlogged)	144,501	10.951	4.565	3.000	8.000	10.000	13.000	25.000
NUMBERCALLS (ln)	144,501	2.154	0.543	0.693	1.792	2.197	2.565	3.178
NUMBERCALLS (unlogged)	144,501	9.814	4.710	2.000	6.000	9.000	13.000	24.000
PREVIOUSPART	144,501	2.058	1.392	0.000	1.000	2.000	3.000	4.000
Q	144,501	2.086	1.399	0.560	1.183	1.630	2.431	8.522
RET	144,501	0.008	0.246	-0.862	-0.112	0.029	0.151	0.668
SALESGROWTH	144,501	0.046	0.124	-0.202	-0.007	0.026	0.070	0.837
SIZE	144,501	7.609	1.713	3.325	6.385	7.534	8.702	13.049
STARANALYST	144,501	0.034	0.181	0.000	0.000	0.000	0.000	1.000
STDEARN	144,501	0.016	0.024	0.000	0.004	0.008	0.018	0.170
TOTRISK	144,501	-0.011	0.855	-1.135	-0.605	-0.215	0.348	3.802

This table shows descriptive statistics for all variables used in the main model. All continuous variables are winsorized at the 1st and 99th percentiles. All variables are as defined in Appendix 1. For analyst control variables that we include in our regression models in a logged form (ln), we also report those variables here in their respective unlogged form.

Table 3: Pearson correlations

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)
(1) DIRECTNESS	**1.000**													
(2) FOLLOWUP	**-0.142**	**1.000**												
(3) NEGATIVEQ	**-0.033**	**0.129**	**1.000**											
(4) PREFACE	**-0.033**	**0.203**	**0.056**	**1.000**										
(5) AGGRSCORE	**0.446**	**0.584**	**0.474**	**0.572**	**1.000**									
(6) HIGHAGGR	**0.233**	**0.583**	**0.218**	**0.602**	**0.794**	**1.000**								
(7) MALEANALYST	**0.017**	**0.030**	**0.008**	**0.025**	**0.040**	**0.037**	**1.000**							
(8) MALECEO	**-0.007**	**0.019**	0.001	**0.008**	**0.010**	**0.012**	**0.031**	**1.000**						
(9) ACCURACY	0.005	-0.003	-0.002	0.001	0.001	0.000	0.006	0.003	**1.000**					
(10) AF	**0.026**	**-0.013**	-0.004	**0.010**	**0.011**	0.003	**0.011**	-0.002	0.003	**1.000**				
(11) AFE	0.001	**0.008**	**0.012**	**-0.008**	0.006	0.005	0.000	0.004	-0.003	**-0.148**	**1.000**			
(12) ANALYSTMULTIND	-0.006	**0.013**	0.004	**0.007**	**0.009**	**0.008**	0.004	0.002	-0.004	**0.014**	-0.002	**1.000**		
(13) AWARDBEFORE	0.001	**-0.034**	**0.024**	0.004	-0.006	**-0.017**	0.006	0.001	-0.001	**0.058**	0.001	**0.024**	**1.000**	
(14) BROKERAWARDS	**0.016**	**-0.061**	0.001	-0.001	**-0.023**	**-0.029**	**0.014**	-0.005	-0.004	**0.066**	0.001	**0.023**	**0.459**	**1.000**
(15) BROKERSIZE	0.005	**-0.027**	**-0.008**	**0.016**	-0.007	-0.005	**0.026**	-0.001	0.000	**0.054**	0.003	**0.080**	**0.205**	**0.531**
(16) BUSSEG	**-0.009**	**0.027**	**0.011**	**0.016**	**0.021**	**0.021**	**-0.019**	-0.006	-0.004	**0.151**	-0.006	**0.012**	**0.073**	**0.056**
(17) CEOLENGTH	0.003	**-0.016**	-0.003	**-0.008**	**-0.012**	**-0.009**	0.005	**-0.007**	0.002	**-0.053**	**0.017**	0.000	**-0.014**	-0.004
(18) CEONEGATIVE	-0.003	**0.050**	**0.033**	0.006	**0.040**	**0.032**	**-0.009**	**0.030**	-0.003	**-0.014**	**0.097**	0.005	**0.020**	**0.020**
(19) CEOPOSITIVE	**0.014**	**-0.050**	**-0.022**	0.007	**-0.024**	**-0.022**	**-0.021**	**-0.008**	-0.002	**0.062**	**-0.071**	**0.013**	**0.024**	**0.024**
(20) DELTAEARN	0.000	-0.001	0.000	0.003	0.001	0.004	0.004	-0.004	-0.002	**0.055**	**-0.160**	0.002	-0.002	-0.003
(21) EARN	**0.011**	**-0.016**	-0.006	0.002	-0.004	-0.005	**0.009**	**-0.023**	-0.001	**0.473**	**-0.149**	**0.013**	**0.044**	**0.048**
(22) FIRMEXPERIENCE	0.000	**0.014**	**0.030**	**0.025**	**0.030**	**0.022**	**0.011**	0.002	-0.006	**0.063**	-0.003	**0.165**	**0.108**	**0.038**
(23) GENERALEXPERIENCE	**0.020**	-0.001	**0.010**	**0.025**	**0.026**	**0.017**	**0.017**	**-0.016**	-0.001	**0.028**	-0.006	**0.169**	**0.051**	0.005
(24) GEOSEG	**-0.014**	**0.010**	**-0.015**	**0.014**	-0.001	**0.010**	**0.030**	**0.047**	-0.001	**0.046**	**-0.027**	**0.011**	0.003	**-0.007**
(25) LOSS	**-0.017**	**0.010**	0.004	-0.004	-0.004	-0.001	**-0.012**	**0.009**	-0.002	**-0.478**	**0.162**	**-0.013**	**-0.059**	**-0.065**
(26) MV	**0.089**	**-0.193**	**-0.058**	**-0.057**	**-0.101**	**-0.110**	**-0.009**	-0.004	0.004	**0.276**	**-0.028**	**0.019**	**0.202**	**0.260**
(27) NUMBERANALYSTS	**0.060**	**-0.153**	**-0.047**	**-0.097**	**-0.109**	**-0.114**	**-0.024**	**-0.022**	**0.011**	**0.093**	0.006	**0.038**	**0.120**	**0.173**
(28) NUMBERCALLS	**-0.017**	**0.050**	**0.024**	**0.034**	**0.042**	**0.041**	**0.008**	0.002	**-0.008**	**0.044**	0.001	**0.520**	**0.103**	**0.091**
(29) PREVIOUSPART	**-0.029**	**0.059**	**0.030**	**0.047**	**0.048**	**0.048**	-0.005	-0.002	-0.003	**0.032**	-0.001	**0.191**	**0.044**	**0.021**
(30) Q	**0.012**	**-0.062**	**-0.021**	**-0.028**	**-0.047**	**-0.043**	0.001	**-0.020**	-0.001	**-0.143**	**-0.013**	**-0.010**	**-0.050**	**-0.019**
(31) RET	**0.008**	**-0.013**	**-0.009**	**0.008**	-0.002	-0.001	**0.009**	0.003	-0.001	**0.095**	**-0.076**	**-0.010**	-0.004	**-0.013**
(32) SALESGROWTH	**-0.012**	**-0.012**	-0.006	-0.005	**-0.017**	**-0.013**	-0.007	0.001	0.000	**-0.110**	**-0.070**	**-0.011**	**-0.032**	**-0.031**
(33) SIZE	**0.085**	**-0.146**	**-0.042**	**-0.043**	**-0.065**	**-0.078**	**-0.008**	-0.001	0.004	**0.298**	**0.008**	**0.020**	**0.211**	**0.257**
(34) STARANALYST	-0.007	**-0.014**	**0.024**	**0.011**	0.004	-0.005	-0.004	**0.009**	0.004	**0.035**	0.004	**0.019**	**0.625**	**0.375**
(35) STDEARN	**-0.030**	0.006	0.002	-0.002	**-0.013**	-0.004	**-0.021**	**-0.009**	0.000	**-0.269**	**-0.014**	**-0.016**	**-0.051**	**-0.062**
(36) TOTRISK	**-0.051**	**0.060**	**0.027**	-0.002	**0.013**	**0.021**	**-0.011**	**-0.014**	-0.003	**-0.303**	**0.018**	**-0.013**	**-0.074**	**-0.101**

Variables	(15)	(16)	(17)	(18)	(19)	(20)	(21)	(22)	(23)	(24)	(25)	(26)	(27)	(28)
(15) BROKERSIZE	**1.000**													
(16) BUSSEG	**0.046**	**1.000**												
(17) CEOLENGTH	0.001	**0.028**	**1.000**											
(18) CEONEGATIVE	**0.012**	**0.081**	**-0.108**	**1.000**										
(19) CEOPOSITIVE	**0.035**	**0.033**	**-0.166**	**-0.147**	**1.000**									
(20) DELTAEARN	-0.005	-0.002	**-0.008**	**-0.040**	**0.019**	**1.000**								
(21) EARN	**0.041**	**0.099**	**-0.043**	**-0.075**	**0.070**	**0.399**	**1.000**							
(22) FIRMEXPERIENCE	**0.089**	**0.088**	-0.006	**0.039**	**0.046**	-0.004	**0.055**	**1.000**						
(23) GENERALEXPERIENCE	**0.085**	**0.031**	0.004	**0.007**	**0.033**	-0.002	**0.009**	**0.551**	**1.000**					
(24) GEOSEG	0.001	**0.162**	**0.039**	**-0.040**	**0.031**	0.001	**0.072**	**0.049**	**0.023**	**1.000**				
(25) LOSS	**-0.057**	**-0.133**	**0.058**	**0.040**	**-0.055**	**-0.218**	**-0.649**	**-0.065**	**-0.009**	**-0.040**	**1.000**			
(26) MV	**0.164**	**0.208**	**-0.023**	**-0.059**	**0.108**	0.005	**0.256**	**0.132**	**0.055**	**0.132**	**-0.279**	**1.000**		
(27) NUMBERANALYSTS	**0.135**	0.004	**-0.046**	-0.003	**0.051**	-0.002	**0.132**	**0.031**	**-0.010**	**0.037**	**-0.108**	**0.455**	**1.000**	
(28) NUMBERCALLS	**0.214**	**0.064**	**-0.009**	**0.052**	**0.022**	-0.006	**0.035**	**0.237**	**0.199**	**0.012**	**-0.048**	**0.035**	**0.104**	**1.000**
(29) PREVIOUSPART	**0.075**	**0.051**	**-0.015**	**0.024**	**0.019**	**-0.007**	**0.034**	**0.583**	**0.343**	**0.037**	**-0.035**	**0.010**	**-0.017**	**0.282**
(30) Q	0.001	**-0.213**	**0.014**	**-0.212**	**-0.019**	**0.011**	**0.038**	**-0.081**	**-0.021**	**0.015**	**0.063**	**0.125**	**0.111**	**-0.055**
(31) RET	**-0.016**	**0.014**	**-0.028**	**-0.147**	**0.082**	**0.064**	**0.105**	0.002	**0.016**	**0.017**	**-0.084**	**0.146**	**-0.063**	**-0.055**
(32) SALESGROWTH	**-0.024**	**-0.083**	**0.015**	**-0.152**	**-0.023**	**0.099**	**0.009**	**-0.075**	**-0.029**	**-0.072**	**0.016**	**-0.052**	**-0.012**	**-0.039**
(33) SIZE	**0.151**	**0.288**	**-0.040**	**0.123**	**0.089**	-0.006	**0.146**	**0.146**	**0.060**	**0.038**	**-0.242**	**0.808**	**0.328**	**0.056**
(34) STARANALYST	**0.162**	**0.044**	**-0.014**	**0.022**	0.006	-0.001	**0.030**	**0.078**	**0.051**	0.007	**-0.038**	**0.125**	**0.094**	**0.088**
(35) STDEARN	**-0.065**	**-0.129**	**0.044**	**-0.051**	**-0.038**	**0.007**	**-0.314**	**-0.076**	**-0.022**	**-0.008**	**0.311**	**-0.218**	**-0.087**	**-0.054**
(36) TOTRISK	**-0.093**	**-0.144**	**0.031**	**0.141**	**-0.106**	-0.004	**-0.276**	**-0.102**	**-0.036**	**-0.042**	**0.312**	**-0.440**	**-0.057**	**-0.025**

Variables	(29)	(30)	(31)	(32)	(33)	(34)	(35)	(36)
(29) PREVIOUSPART	**1.000**							
(30) Q	**-0.026**	**1.000**						
(31) RET	-0.005	**0.194**	**1.000**					
(32) SALESGROWTH	**-0.042**	**0.170**	**0.038**	**1.000**				
(33) SIZE	**0.012**	**-0.355**	0.005	**-0.147**	**1.000**			
(34) STARANALYST	**0.048**	**-0.035**	**-0.012**	**-0.021**	**0.132**	**1.000**		
(35) STDEARN	**-0.035**	**0.193**	**-0.020**	**0.224**	**-0.298**	**-0.031**	**1.000**	
(36) TOTRISK	**-0.031**	**-0.028**	**-0.263**	**0.049**	**-0.329**	**-0.030**	**0.299**	**1.000**

All continuous variables are winsorized at the 1st and 99th percentiles. Bold font indicates pairwise Pearson correlations at the 1 percent significance level. All variables are as defined in Appendix 1.

Table 4: Univariate statistics for analyst questions and gender styles

Variable	Female analysts (N = 16,828)	Male analysts (N = 127,673)	Difference (N=144,501)
DIRECTNESS	0.353	0.379	0.026***
FOLLOWUP	0.666	0.709	0.043***
NEGATIVEQ	0.137	0.146	0.009***
PREFACE	0.760	0.792	0.032***
AGGRSCORE	1.956	2.026	0.110***
HIGHAGGR (AGGRSCORE>=2)	0.701	0.751	0.050***

This table compares group mean values for male and female analysts for our verbal aggressiveness measures as defined in Appendix 1. Asterisks indicate whether the difference between the two mean values has significant p-values <0.01 (***), <0.05 (**), and <0.1 (*) (two-sided test statistics).

Table 5: Verbal aggressiveness and analyst gender

	(1) DIRECTNESS	(2) FOLLOWUP	(3) NEGATIVEQ	(4) PREFACE	(5) AGGRSCORE	(6) HIGHAGGR
MALEANALYST	0.026***	0.036***	0.009***	0.028***	0.100***	0.044***
	(0.000)	(0.000)	(0.008)	(0.000)	(0.000)	(0.000)
ACCURACY	0.004	-0.001	-0.001	0.001	0.004	0.001
	(0.209)	(0.818)	(0.790)	(0.559)	(0.450)	(0.651)
AF	0.174*	0.125	0.087	0.259***	0.644***	0.171
	(0.091)	(0.315)	(0.239)	(0.006)	(0.002)	(0.101)
AFE	-0.101	0.215	0.444***	-0.206	0.352	0.214
	(0.577)	(0.279)	(0.003)	(0.212)	(0.313)	(0.216)
ANALYSTMULTIND	0.006	-0.030***	-0.021***	-0.019**	-0.064***	-0.030***
	(0.508)	(0.000)	(0.001)	(0.017)	(0.000)	(0.000)
AWARDBEFORE	-0.012	-0.008	0.027***	0.004	0.012	-0.008
	(0.177)	(0.366)	(0.000)	(0.555)	(0.479)	(0.346)
BROKERAWARDS	0.002**	-0.005***	0.000	0.002*	-0.001	-0.001
	(0.043)	(0.000)	(0.809)	(0.052)	(0.767)	(0.569)
BROKERSIZE	-0.004***	0.002*	-0.002***	0.003***	-0.002	0.001
	(0.000)	(0.073)	(0.008)	(0.009)	(0.415)	(0.340)
BUSSEG	-0.019***	0.028***	0.007**	0.007	0.024*	0.015**
	(0.000)	(0.001)	(0.029)	(0.124)	(0.068)	(0.014)
CEOLENGTH	0.009***	-0.019***	-0.003	-0.006**	-0.020***	-0.010***
	(0.006)	(0.000)	(0.172)	(0.029)	(0.008)	(0.006)
CEONEGATIVE	0.005	0.009**	0.010***	0.001	0.024***	0.008***
	(0.106)	(0.024)	(0.000)	(0.816)	(0.000)	(0.009)
CEOPOSITIVE	-0.000	-0.008***	-0.004***	0.001	-0.011**	-0.004*
	(0.836)	(0.005)	(0.007)	(0.448)	(0.014)	(0.050)
DELTAEARN	0.037	0.032	0.031	-0.019	0.081	0.075
	(0.504)	(0.620)	(0.453)	(0.731)	(0.471)	(0.180)
EARN	-0.126*	-0.133	-0.007	0.020	-0.246	-0.106
	(0.085)	(0.178)	(0.896)	(0.754)	(0.142)	(0.182)
FIRMEXPERIENCE	-0.002	0.002	0.009***	-0.002	0.008**	0.001
	(0.434)	(0.345)	(0.000)	(0.285)	(0.026)	(0.482)
GENERALEXPERIENCE	0.005*	-0.003	0.003*	-0.008***	-0.003	-0.004*
	(0.072)	(0.210)	(0.064)	(0.000)	(0.493)	(0.072)
GEOSEG	0.001	0.003	-0.008***	0.003	-0.001	0.006
	(0.843)	(0.691)	(0.008)	(0.474)	(0.928)	(0.229)
LOSS	0.002	-0.017***	-0.002	-0.011**	-0.029***	-0.016***
	(0.752)	(0.007)	(0.571)	(0.021)	(0.007)	(0.002)
MV	0.000	-0.034***	-0.003	-0.012***	-0.049***	-0.023***
	(0.946)	(0.000)	(0.377)	(0.002)	(0.000)	(0.000)
NUMBERANALYSTS	0.090***	-0.127***	-0.039***	-0.089***	-0.165***	-0.089***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
NUMBERCALLS	-0.009**	0.033***	0.013***	0.015***	0.052***	0.025***
	(0.026)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
PREVIOUSPART	-0.009***	0.014***	0.002*	0.011***	0.018***	0.010***
	(0.000)	(0.000)	(0.063)	(0.000)	(0.000)	(0.000)
Q	0.007***	-0.001	-0.001	-0.002	0.003	0.000

	(0.001)	(0.812)	(0.445)	(0.311)	(0.611)	(0.937)
RET	-0.015**	0.024***	0.001	0.026***	0.035**	0.022***
	(0.033)	(0.003)	(0.900)	(0.000)	(0.013)	(0.002)
SALESGROWTH	-0.007	-0.010	-0.004	0.010	-0.011	-0.002
	(0.626)	(0.539)	(0.656)	(0.424)	(0.658)	(0.849)
SIZE	0.011***	-0.014**	-0.007***	0.001	-0.009	-0.006
	(0.003)	(0.026)	(0.007)	(0.827)	(0.345)	(0.182)
STARANALYST	-0.022**	0.023**	0.027***	0.033***	0.060***	0.024**
	(0.035)	(0.038)	(0.001)	(0.000)	(0.006)	(0.020)
STDEARN	-0.120*	-0.237**	-0.064	-0.060	-0.482***	-0.148**
	(0.095)	(0.019)	(0.222)	(0.340)	(0.001)	(0.046)
TOTRISK	-0.007**	-0.014***	0.004	-0.002	-0.019***	-0.009***
	(0.025)	(0.002)	(0.108)	(0.545)	(0.009)	(0.005)
INDUSTRY FE	YES	YES	YES	YES	YES	YES
YEAR-QUARTER FE	YES	YES	YES	YES	YES	YES
INTERCEPT	YES	YES	YES	YES	YES	YES
Observations	144,501	144,501	144,501	144,501	144,501	144,501
Adjusted R-squared	0.024	0.082	0.014	0.026	0.038	0.038

This table presents the results for tests of the verbal aggressiveness of analyst questions regressed on the gender of the analyst as our variable of interest. All continuous variables are winsorized at the 1st and 99th percentiles. All variables are as defined in Appendix 1. INDUSTRY FE are based on Fama-French 48 industries. Asterisks indicate significance levels: *** p<0.01, ** p<0.05, and * p<0.1 (two-sided test statistics) for all variables. We report p-values in parentheses below the coefficients and cluster standard errors at the firm level.

Table 6: Verbal aggressiveness and the gender of CEOs and analysts

	(1) DIRECTNESS	(2) FOLLOWUP	(3) NEGATIVEQ	(4) PREFACE	(5) AGGRSCORE	(6) HIGHAGGR
MALEANALYST	0.053***	0.095***	0.018	0.034**	0.178***	0.070***
	(0.002)	(0.002)	(0.116)	(0.044)	(0.000)	(0.000)
MALECEO	0.011	0.067**	0.003	0.005	0.064	0.026
	(0.221)	(0.022)	(0.806)	(0.774)	(0.173)	(0.220)
MALEANALYST * MALECEO	-0.024†	-0.065†††	-0.009	-0.005	-0.079††	-0.027†
	(0.069)	(0.010)	(0.232)	(0.381)	(0.039)	(0.090)
ACCURACY	0.004	-0.001	-0.001	0.001	0.004	0.001
	(0.206)	(0.827)	(0.795)	(0.558)	(0.443)	(0.646)
AF	0.173*	0.118	0.087	0.258***	0.640***	0.169
	(0.093)	(0.341)	(0.240)	(0.006)	(0.002)	(0.104)
AFE	-0.100	0.212	0.445***	-0.205	0.353	0.214
	(0.581)	(0.285)	(0.003)	(0.215)	(0.311)	(0.216)
ANALYSTMULTIND	0.006	-0.029***	-0.021***	-0.019**	-0.064***	-0.030***
	(0.510)	(0.000)	(0.001)	(0.017)	(0.000)	(0.000)
AWARDBEFORE	-0.012	-0.007	0.027***	0.004	0.012	-0.007
	(0.172)	(0.423)	(0.000)	(0.555)	(0.478)	(0.349)
BROKERAWARDS	0.002**	-0.005***	0.000	0.002**	-0.001	-0.001
	(0.042)	(0.000)	(0.808)	(0.048)	(0.792)	(0.597)
BROKERSIZE	-0.005***	0.002*	-0.002***	0.003**	-0.002	0.001
	(0.000)	(0.077)	(0.008)	(0.010)	(0.384)	(0.366)
BUSSEG	-0.019***	0.027***	0.007**	0.008	0.024*	0.015**
	(0.000)	(0.002)	(0.031)	(0.118)	(0.066)	(0.013)
CEOLENGTH	0.009***	-0.019***	-0.003	-0.006**	-0.019***	-0.010***
	(0.006)	(0.000)	(0.172)	(0.029)	(0.008)	(0.006)
CEONEGATIVE	0.005*	0.009**	0.010***	0.001	0.025***	0.008***
	(0.090)	(0.026)	(0.000)	(0.806)	(0.000)	(0.009)
CEOPOSITIVE	-0.000	-0.008***	-0.004***	0.001	-0.011**	-0.004*
	(0.855)	(0.005)	(0.008)	(0.441)	(0.015)	(0.052)
DELTAEARN	0.036	0.030	0.031	-0.020	0.078	0.073
	(0.505)	(0.643)	(0.451)	(0.722)	(0.489)	(0.190)
EARN	-0.127*	-0.130	-0.008	0.021	-0.243	-0.104
	(0.081)	(0.189)	(0.881)	(0.748)	(0.147)	(0.190)
FIRMEXPERIENCE	-0.002	0.002	0.009***	-0.002	0.008**	0.001
	(0.436)	(0.325)	(0.000)	(0.286)	(0.026)	(0.487)
GENERALEXPERIENCE	0.005*	-0.003	0.003*	-0.008***	-0.003	-0.004*
	(0.078)	(0.252)	(0.066)	(0.000)	(0.474)	(0.070)
GEOSEG	0.001	0.003	-0.008***	0.003	-0.001	0.006
	(0.837)	(0.671)	(0.008)	(0.483)	(0.924)	(0.233)
LOSS	0.002	-0.017***	-0.002	-0.011**	-0.029***	-0.016***
	(0.758)	(0.006)	(0.566)	(0.020)	(0.006)	(0.002)
MV	0.000	-0.034***	-0.002	-0.012***	-0.049***	-0.023***
	(0.944)	(0.000)	(0.378)	(0.002)	(0.000)	(0.000)
NUMBERANALYSTS	0.090***	-0.127***	-0.039***	-0.089***	-0.164***	-0.089***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
NUMBERCALLS	-0.009**	0.032***	0.013***	0.015***	0.052***	0.025***

	(0.027)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
PREVIOUSPART	-0.009***	0.014***	0.002*	0.011***	0.017***	0.010***
	(0.000)	(0.000)	(0.064)	(0.000)	(0.000)	(0.000)
Q	0.007***	-0.001	-0.001	-0.002	0.003	0.000
	(0.001)	(0.814)	(0.436)	(0.316)	(0.605)	(0.924)
RET	-0.015**	0.023***	0.001	0.026***	0.035**	0.022***
	(0.033)	(0.003)	(0.901)	(0.000)	(0.014)	(0.002)
SALESGROWTH	-0.006	-0.010	-0.004	0.010	-0.011	-0.002
	(0.644)	(0.530)	(0.669)	(0.421)	(0.669)	(0.851)
SIZE	0.011***	-0.014**	-0.007***	0.001	-0.009	-0.006
	(0.003)	(0.024)	(0.007)	(0.825)	(0.347)	(0.184)
STARANALYST	-0.022**	0.021*	0.027***	0.033***	0.060***	0.024**
	(0.037)	(0.060)	(0.001)	(0.000)	(0.006)	(0.020)
STDEARN	-0.123*	-0.236**	-0.065	-0.061	-0.484***	-0.148**
	(0.090)	(0.019)	(0.213)	(0.337)	(0.001)	(0.045)
TOTRISK	-0.007**	-0.014***	0.004	-0.002	-0.018**	-0.009***
	(0.026)	(0.002)	(0.108)	(0.559)	(0.010)	(0.006)
INDUSTRY FE	YES	YES	YES	YES	YES	YES
YEAR-QUARTER FE	YES	YES	YES	YES	YES	YES
INTERCEPT	YES	YES	YES	YES	YES	YES
Observations	144,501	144,501	144,501	144,501	144,501	144,501
Adjusted R-squared	0.024	0.082	0.014	0.026	0.038	0.038

This table presents the results of tests of the verbal aggressiveness of analyst questions regressed on the gender of the analysts conditioned on the gender of the CEO. All continuous variables are winsorized at the 1st and 99th percentiles. All variables are as defined in Appendix 1. INDUSTRY FE are based on Fama-French 48 industries. Asterisks indicate significance levels: *** p<0.01, ** p<0.05, and * p<0.1 (two-sided test statistics). As our hypothesis two is one-sided (e.g., out-of-group bias), we report one-sided test statistics for the interaction term *MALEANALYST * MALECEO* with significance levels of ††† p<0.01, †† p<0.05, and † p<0.1. We report p-values in parentheses below the coefficients and cluster standard errors at the firm-level.

Table 7: Panel A: CEO gender selection model

	Dependent variable: MALECEO
INDEPENDENT VARIABLES	
EXCLUSION RESTRICTIONS	
MALESHARECOUNTY	1.353
	(0.300)
MALESHAREINDUSTRY	0.885**
	(0.048)
FURTHER CONTROLS	
AF	0.837
	(0.300)
CGOV	0.042
	(0.528)
DELTAEARN	0.323
	(0.343)
EARN	-0.307
	(0.614)
Q	0.005
	(0.793)
RET	0.034
	(0.302)
SIZE	0.019*
	(0.097)
INDUSTRY FE	YES
YEAR FE	YES
INTERCEPT	YES
Observations	55,979
Pseudo R-squared	0.0255***

This table presents the regression results for the CEO selection model employing a probit estimation. *MALESHARECOUNTY* (*MALESHAREINDUSTRY*) is defined as the share of male employees in a county (industry) in a year, and *CGOV* is the corporate governance strength score from KLD MSCI. All further variables are as defined in Appendix 1. All independent variables are lagged one period. Asterisks indicate significance levels: *** p<0.01, ** p<0.05, and * p<0.1 (two-sided test statistics). We report significance levels in parentheses below the coefficients. Standard errors are clustered at the firm level.

Panel B: Verbal aggressiveness and the gender of CEOs and analysts with inverse Mills' ratio

	(1) DIRECTNESS	(2) FOLLOWUP	(3) NEGATIVEQ	(4) PREFACE	(5) AGGRSCORE	(6) HIGHAGGR
MALEANALYST	0.079***	0.091***	0.026	0.032*	0.158***	0.081***
	(0.002)	(0.004)	(0.134)	(0.098)	(0.002)	(0.008)
MALECEO	0.050**	0.053	0.034**	-0.008	0.050	0.045
	(0.026)	(0.128)	(0.040)	(0.718)	(0.340)	(0.166)
MALEANALYST * MALECEO	-0.050††	-0.054††	-0.009	0.009	-0.059†	-0.035†
	(0.019)	(0.048)	(0.116)	(0.330)	(0.056)	(0.066)
ACCURACY	0.000	-0.001	-0.002	0.003	0.000	0.001
	(0.960)	(0.731)	(0.491)	(0.378)	(0.970)	(0.836)
AF	0.226*	-0.057	0.092	0.137	0.402	0.067
	(0.093)	(0.706)	(0.320)	(0.217)	(0.108)	(0.580)
AFE	-0.187	0.217	0.367**	-0.216	0.177	0.125
	(0.435)	(0.388)	(0.044)	(0.308)	(0.693)	(0.567)
ANALYSTMULTIND	0.015	-0.036***	-0.019**	-0.023**	-0.063***	-0.027***
	(0.158)	(0.000)	(0.014)	(0.015)	(0.002)	(0.006)
AWARDBEFORE	-0.014	-0.002	0.024***	-0.012	-0.009	-0.018*
	(0.193)	(0.875)	(0.001)	(0.197)	(0.668)	(0.072)
BROKERAWARDS	0.003**	-0.004***	0.002*	0.002*	0.003	0.000
	(0.023)	(0.002)	(0.071)	(0.069)	(0.224)	(0.772)
BROKERSIZE	-0.005***	0.002	-0.003**	0.004***	-0.002	0.002
	(0.002)	(0.280)	(0.012)	(0.002)	(0.436)	(0.137)
BUSSEG	-0.018***	0.029***	0.008*	0.007	0.026*	0.016**
	(0.004)	(0.004)	(0.052)	(0.267)	(0.095)	(0.031)
CEOLENGTH	0.009**	-0.024***	-0.004	-0.008**	-0.026***	-0.015***
	(0.028)	(0.000)	(0.171)	(0.024)	(0.003)	(0.000)
CEONEGATIVE	0.004	0.010**	0.011***	-0.002	0.023***	0.008**
	(0.336)	(0.028)	(0.000)	(0.564)	(0.004)	(0.039)
CEOPOSITIVE	0.000	-0.007**	-0.004**	0.002	-0.008	-0.002
	(0.994)	(0.043)	(0.025)	(0.299)	(0.142)	(0.526)
DELTAEARN	0.076	0.039	-0.014	0.003	0.093	0.072
	(0.231)	(0.597)	(0.795)	(0.964)	(0.500)	(0.279)
EARN	-0.200**	-0.007	0.019	0.067	-0.102	0.021
	(0.019)	(0.949)	(0.773)	(0.373)	(0.593)	(0.814)
FIRMEXPERIENCE	-0.001	0.002	0.009***	-0.003	0.009**	0.002
	(0.799)	(0.328)	(0.000)	(0.181)	(0.043)	(0.435)
GENERALEXPERIENCE	0.004	-0.005	0.004*	-0.006*	-0.002	-0.004
	(0.270)	(0.199)	(0.061)	(0.051)	(0.763)	(0.246)
GEOSEG	0.003	0.003	-0.009**	0.004	0.002	0.006
	(0.604)	(0.756)	(0.021)	(0.456)	(0.895)	(0.393)
LOSS	-0.002	-0.019**	-0.001	-0.005	-0.027**	-0.009
	(0.760)	(0.011)	(0.758)	(0.386)	(0.039)	(0.145)
MV	-0.006	-0.035***	0.000	-0.009*	-0.052***	-0.021***
	(0.256)	(0.000)	(0.987)	(0.074)	(0.000)	(0.001)
NUMBERANALYSTS	0.091***	-0.126***	-0.039***	-0.089***	-0.162***	-0.089***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
NUMBERCALLS	-0.008*	0.032***	0.012***	0.016***	0.052***	0.024***

	(0.092)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
PREVIOUSPART	-0.011***	0.014***	0.002*	0.012***	0.017***	0.011***
	(0.000)	(0.000)	(0.056)	(0.000)	(0.000)	(0.000)
Q	0.009***	0.001	-0.003	-0.004	0.004	-0.001
	(0.000)	(0.904)	(0.160)	(0.125)	(0.610)	(0.751)
RET	-0.007	0.015	-0.005	0.024***	0.029	0.018**
	(0.416)	(0.140)	(0.485)	(0.003)	(0.104)	(0.041)
SALESGROWTH	-0.009	-0.019	-0.011	0.002	-0.038	-0.008
	(0.623)	(0.339)	(0.390)	(0.916)	(0.220)	(0.594)
SIZE	0.017***	-0.017**	-0.012***	-0.003	-0.014	-0.013**
	(0.000)	(0.019)	(0.000)	(0.538)	(0.231)	(0.018)
STARANALYST	-0.022*	0.016	0.031***	0.048***	0.077***	0.036***
	(0.078)	(0.231)	(0.003)	(0.000)	(0.003)	(0.003)
STDEARN	-0.194**	-0.058	-0.070	0.004	-0.327*	-0.073
	(0.031)	(0.615)	(0.264)	(0.964)	(0.061)	(0.401)
TOTRISK	-0.005	-0.019***	0.004	-0.003	-0.023***	-0.011***
	(0.154)	(0.000)	(0.100)	(0.415)	(0.006)	(0.007)
INVERSE MILLS RATIO	-0.004***	-0.009***	-0.003***	-0.003***	-0.012***	-0.006***
	(0.006)	(0.000)	(0.001)	(0.013)	(0.000)	(0.000)
INDUSTRY FE	YES	YES	YES	YES	YES	YES
YEAR-QUARTER FE	YES	YES	YES	YES	YES	YES
INTERCEPT	YES	YES	YES	YES	YES	YES
Observations	93,148	93,148	93,148	93,148	93,148	93,148
Adjusted R-squared	0.023	0.082	0.014	0.028	0.039	0.039

This table presents the results of tests of the verbal aggressiveness of analyst questions regressed on the gender of the analysts conditioned on the gender of the CEO. All continuous variables are winsorized at the 1st and 99th percentiles. *INVERSE MILLS RATIO* is the inverse Mills' ratio estimate in Panel A. All other variables are as defined in Appendix 1. INDUSTRY FE are based on Fama-French 48 industries. Asterisks indicate significance levels: *** p<0.01, ** p<0.05, and * p<0.1 (two-sided test statistics). As our hypothesis two is one-sided (e.g., out-of-group bias), we report one-sided test statistics for the interaction term *MALEANALYST* * *MALECEO* with significance levels of ††† p<0.01, †† p<0.05, and † p<0.1. We report p-values in parentheses below the coefficients and cluster standard errors at the firm level.

Table 8: Likelihood of becoming a top-three, star analyst: verbal aggressiveness and analyst gender

Dependent variable: STARANALYST	(1)	(2)	(3)	(4)
DIRECTNESS	2.150**			2.664**
	(0.034)			(0.018)
FOLLOWUP	2.289***			2.162**
	(0.003)			(0.039)
NEGATIVEQ	2.202**			3.879***
	(0.027)			(0.000)
PREFACE	0.742			1.203
	(0.607)			(0.356)
DIRECTNESS * MALEANALYST	-2.784**			-3.405***
	(0.013)			(0.006)
FOLLOWUP * MALEANALYST	-1.813**			-1.970*
	(0.048)			(0.093)
NEGATIVEQ * MALEANALYST	-2.462**			-3.635***
	(0.040)			(0.007)
PREFACE * MALEANALYST	0.034			-0.293
	(0.982)			(0.833)
AGGRSCORE		1.809***		
		(0.000)		
AGGRSCORE * MALEANALYST		-1.553***		
		(0.001)		
HIGHAGGR			1.488***	
			(0.002)	
HIGHAGGR * MALEANALYST			-1.462***	
			(0.006)	
DIRECTNESS * HIGHFEMALESHARE				-1.575
				(0.354)
FOLLOWUP * HIGHFEMALESHARE				-0.421
				(0.801)
NEGATIVEQ * HIGHFEMALESHARE				-2.536
				(0.117)
PREFACE * HIGHFEMALESHARE				-0.811
				(0.781)
DIRECTNESS * MALEANALYST * HIGHFEMALESHARE				2.806
				(0.152)
FOLLOWUP * MALEANALYST * HIGHFEMALESHARE				1.841
				(0.339)
NEGATIVEQ * MALEANALYST * HIGHFEMALESHARE				1.052
				(0.634)
PREFACE * MALEANALYST * HIGHFEMALESHARE				-0.017
				(0.996)
HIGHFEMALESHARE				2.155
				(0.228)
MALEANALYST * HIGHFEMALESHARE				-2.544
				(0.203)

MALEANALYST	2.319**	2.780***	0.639	3.166**
	(0.045)	(0.003)	(0.125)	(0.016)
ACCURACY	0.306	0.289	0.323	0.261
	(0.363)	(0.385)	(0.328)	(0.450)
ANALYSTNEGATIVE	-0.098	-0.107	-0.055	-0.070
	(0.619)	(0.569)	(0.766)	(0.718)
ANALYSTPOSITIVE	0.064	0.055	0.064	0.051
	(0.554)	(0.619)	(0.556)	(0.651)
ANALYSTPRAISE	0.779	0.822	0.692	0.629
	(0.203)	(0.189)	(0.264)	(0.319)
AWARDBEFORE	4.498***	4.437***	4.410***	4.514***
	(0.000)	(0.000)	(0.000)	(0.000)
BROKERAWARDS	0.699***	0.692***	0.687***	0.690***
	(0.000)	(0.000)	(0.000)	(0.000)
BROKERSIZE	-0.343***	-0.325***	-0.332***	-0.330***
	(0.003)	(0.004)	(0.003)	(0.004)
FIRMEXPERIENCE	0.205	0.167	0.135	0.229
	(0.521)	(0.586)	(0.663)	(0.492)
GENERALEXPERIENCE	0.009	0.008	0.009	0.007
	(0.784)	(0.787)	(0.763)	(0.829)
NUMBERCALLS	0.488**	0.487**	0.530**	0.439*
	(0.044)	(0.044)	(0.028)	(0.071)
PREVIOUSPART	-0.120	-0.082	-0.062	-0.161
	(0.350)	(0.518)	(0.620)	(0.230)
INDUSTRY FE	YES	YES	YES	NO
YEAR FE	YES	YES	YES	YES
INTERCEPT	YES	YES	YES	YES
Observations	18,065	18,065	18,065	18,065
Pseudo R-squared	0.644	0.642	0.640	0.641

This table presents the results for the likelihood model of becoming a star analyst. Consequently, the dependent variable *STARANALYST* is a binary variable that indicates whether an analyst is part of the Institutional Investor's list of the top 3 best analysts in a year (a "star" analyst). As the survey for the award is sent to buy-side analysts and portfolio managers in the spring, we use the lead value of *STARANALYST* as the dependent variable. All continuous variables are winsorized at the 1st and 99th percentiles. All variables are included as mean values per analyst-year and otherwise as defined in Appendix 1. *ANALYSTNEGATIVE*, *ANALYSTPOSITIVE*, and *ANALYSTPRAISE* are the share of negative, positive, and praise words spoken by an analyst scaled by their total number of words spoken (and included as mean values per analyst-year). We report two-sided test statistics with significance levels of *** p<0.01, ** p<0.05, and * p<0.1 and show significance levels in parentheses below the coefficients. Industry fixed effects are based on Fama-French 10 industries to match the sector structure of Institutional Investor (results hold for Fama-French 48 industries) and standard errors are clustered at the analyst level. In column (4), we triple interact all verbal aggressiveness and analyst gender variables with *HIGHFEMALESHARE*, which equals 1 (0 otherwise) if the analyst belongs to one of the three industries with the highest share of female analysts (Fama-French 10 industries 1, 6, and 7).

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