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ESG-Related Questions and Their Determinants

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List of Abbreviations

ESG... Environmental, Social, and Governance
MBA .... Master of Business Administration
OLS... Ordinary Least Squares
Q&A .... Questions and Answers
SEC...Securities and Exchange Commission
STEM ....Science, Technology, Engineering, and Mathematics

1 Abstract

I investigate which sociodemographic and professional determinants influence whether equity research analysts ask questions related to environmental, social, or governance (ESG) issues during earnings conference calls. For the analysis of conference call transcripts, I utilize a self-developed algorithm based on FinBERT. Using data from 1,334 conference calls between 2015 and 2021, I find that female analysts ask more frequently about ESG topics, while analysts who began their career during a recession as well as those working for bulge bracket banks ask ESG-related questions less often. For the three subcategories of ESG, I find that analysts with a degree in a technical discipline, those with many All-American research analysts in their firm, and those who have been working for their firm for a longer time ask significantly more questions related to environmental issues. Conversely, having greater work experience, a Master of Business Administration (MBA), or working for a bulge bracket bank is significantly negatively associated with asking environmental questions. For questions related to social issues, I find the same significant determinants as for ESG overall, whereas I fail to find relevant factors for inquiring about corporate governance.

2 Introduction

In this study, I examine the question of who poses ESG-related questions in the questions and answers (Q&A) section of earnings conference calls. The term "ESG" was first introduced in 2004 by the United Nations in a report on the development of financial markets as a distinct concept, with a call to financial institutions, investors, and regulators to develop principles and guidelines for sustainable capital markets (United Nations Global Compact, 2004). Subsequently, investors have increasingly demanded ESG disclosure from companies to effectively incorporate sustainability aspects into investment decisions (Solomon and Solomon, 2006; Moneva and Cuellar, 2009). Despite the Securities and Exchange Commission (SEC) in the USA adopting various initiatives since 2010 for more transparent disclosure of ESG-relevant information,[1] a study by the auditing firm Ernst & Young shows that over 60% of investors believe companies do not adequately disclose their ESG risks (Ernst & Young, 2015). A platform to bridge this information gap regarding ESG is given by the Q&A section

[1] Between 2010 and 2021 the SEC issued its first recommendations for reporting climate-related risks and published multiple proposals to promote ESG disclosures. However, only a few disclosures like the requirement for emissions-intensive companies to release their greenhouse gas emissions were made mandatory. In 2022, the SEC released a new set of regulations that require the disclosure of various sustainability metrics, such as direct and indirect carbon emissions or climate-related financial impacts.

of earnings conference calls. The direct interaction between equity research analysts and the management board provides analysts with the opportunity to enhance the public information base through targeted inquiries and addressing topics with insufficient disclosures by the firm (Mayew, 2008; Matsumoto et al., 2011). The purpose of this study is to identify socio-demographic and professional factors that determine whether an analyst actually uses this platform to ask ESG-related questions. While, apart from gender (Li et al., 2023), there are no other studies examining the relationship between personal characteristics and the posing of ESG-related questions during conference calls, there is evidence from previous accounting and finance literature regarding an association between demographic variables of managers or investors and ESG in other contexts. For instance, management boards with a higher share of female director put a higher emphasis on ESG in their decision making (Hsu et al., 2022) but do not disclose more ESG-information voluntarily (Manita et al., 2018). Manager's network size is another relevant aspect for companies, as a larger network of the board directors is associated with better ESG performance (Harjoto and Wang, 2020) On the buy-side, investors with a degree in science, technology, engineering, or mathematics (STEM) put a stronger emphasis on incorporating ESG into investment decisions (Botsari and Lang, 2020) while the relevance of ESG factors become less relevant in the decision process with the increasing age of an investor (Przychodzen et al., 2016). Accordingly, I examine in this study which of these relationships are applicable to analysts in the context of asking about ESG topics and what further determinants are relevant.

My analysis is based on over 26,000 questions from all available earnings conference call transcripts of the 50 largest companies by market capitalization as of July 1, 2023 in the S&P 500 from 2015 to 2021. Using a self-written algorithm that incorporates the large language model FinBERT-ESG (Huang et al., 2023), I classify the questions based on their ESG content. Subsequently, for a subset of the data, I manually collect information on the respective analysts regarding gender, age, experience, economic conditions at the start of their career, university degrees, and the corporate culture of the companies for which the analysts work. I employ logistic regression to test in five models which factors influence the addressing of ESG topics in general as well as the three subdimensions of environmental, social, and governance. In line with Li et al. (2023), my results show that, on an aggregated level, women significantly more often integrate ESG into their questions. I observe a contrary and also significant effect for analysts who began their first job in the financial sector in a year when there was a recession in the USA and for analysts working at bulge bracket banks, which are recognized as the largest global full-service investment banks. Furthermore, I find differences in the explanatory factors of the subcategories. While the model for social-related questions yields similar results to the general ESG model, additional associations are found for questions related to environmental issues that were not significant or present at all in the aggregated model. One important determinant is the educational background, with STEM degrees having a significantly positive and MBAs having a significantly negative impact on the frequency of asking these questions. Additionally, where and how long an analyst has been working in equity research is relevant for inquiries related to environmental issues. Analysts who work for a firm with many All-American research analysts, an award given by the magazine “Institutional Investor”, and those who have been with their firm for a longer period ask significantly more questions about environmental issues, while analysts from bulge bracket banks and those with more professional experience ask fewer such questions. Finally, I cannot draw conclusions for governance-related questions due to an insufficient number of observations.

I contribute to the literature in a three-fold way. First, my study extends the question initially raised by Li et al. (2023) regarding which analysts ask ESG-related questions in conference calls. I confirm that women do this more frequently, but I also provide a more holistic model that maps many of the potentially relevant sociodemographic and professional determinants and their interdependencies. Second, the study expands research on how personal backgrounds influence actions in financial markets by comparing existing literature on the effects of managers’ or investors’ personal factors with the group of equity research analysts. I identify many similarities, like the analogy that managers with MBA degrees focus more on short-term goals in their decisions paired with less innovative approaches (Hambrick an Mason, 1984) and analysts with an MBA ask fewer questions about, often longer-term, environmental topics. However, my results suggest some differences as well, such as older investors considering ESG themes less in their decisions (Przychodzen et al., 2016), while there is no evidence analysts ask fewer questions about ESG with increasing age. Lastly, my study contributes to the research on the application of natural language processing in the context of textual analysis of conference calls (Price et al., 2012; Comprix et al., 2022). Building on the model developed by Huang et al. (2023), I devise a new approach for measuring ESG themes in conference calls that could be applied to further research.

The rest of the paper is structured as follows: In the next chapter, I discuss prior literature and develop my hypotheses. Subsequently, I present methods, data, and models, as well as the results. The paper ends with a discussion of research limitations and a final conclusion.

3 Literature Review and Hypothesis Development

3.1 Q&A Section of Earnings Conference Calls

Earnings conference calls hold notable importance for market participants and have become a popular way for companies to disclose information since the late 20th century (Bushee et al., 2003; Kimbrough, 2005). By reducing the volume of private information compared to publicly available information, they play a critical role in lowering information asymmetry among investors (Brown et al., 2004). For equity research analysts, the calls provide a valuable source of information as they significantly enhance the quality of earnings forecasts (Bowen et al., 2002). Within these calls, the Q&A segment, which usually follows after a management presentation and enables analysts to interact with the management, has been examined as the most informative part as analysts can provide a distinct added value in the Q&A (Matsumoto et al., 2011). This is because the Q&A, in contrast to the management presentation, is not scripted, making it more challenging for managers to withhold unfavorable news. In this context, verbal cues are particularly informative for market participants, as conference calls are conducted orally and additional information can be derived from tone and linguistic nuances compared to written documents (Mayew and Venkatachalam, 2012).

3.2 ESG Coverage in Conference Calls

One topic that has been increasingly brought up during earnings conference calls is ESG performance and corporate sustainability. While some companies do not see earnings calls as an appropriate platform to discuss long-term trends, including sustainability issues, the overall trend shows the growing importance of ESG discourse for all stakeholders (Setterberg and Sjöström, 2021). From 2015 to 2020, the mention of ESG-related terms increased by 64% in Euro Stoxx 600 conference calls (Konieczny and Weiß, 2023). Christensen et al. (2021) infer an increasing interest in ESG reporting among equity research analysts. This arises from the challenge that analysts face in quantifying ESG performance, thereby rendering conference calls a good setting for gathering pertinent information on the subject

(Bochkay et al., 2021). Henry et al. (2021) further underline the growing relevance of environmental discourse in earnings calls as they show a direct link to firm valuations. Previous studies have shown that talking about corporate sustainability during conference calls also influences analysts' perceptions of a firm. Firms with more ESG disclosure tend to have lower analyst forecast errors (Dhaliwal et al., 2011) while gaining greater analyst coverage (Gao et al., 2016). However, analysts do not only retrieve information from earnings conference calls; they also contribute to enhancing transparency regarding ESG issues. Hail et al. (2021) have pointed out in a recent study that managers, in comparison to analysts, talk more about environmental issues while being more positive about this topic than in discussions about financial performance. This result suggests that some firms might misuse the platform of an earnings call to greenwash their operations. Analysts, in contrast, only ask about this topic if they see it as relevant for their forecasts. Therefore, analysts' questions can provide better insights into a company's actual ESG performance.

3.3 Hypothesis Development

3.3.1 Gender

In this thesis, I investigate which sociodemographic and personal factors influence whether or not an analyst asks questions related to ESG during the Q&A part of earnings conference calls. To my knowledge as of January 2024, there is only one study that researches a similar question. Li et al. (2023) find that the gender of an analyst impacts their likelihood of asking questions about environmental or social issues. Female analysts are significantly more likely than their male counterparts to inquire about these topics. This is in line with the overall association between gender and ESG shown in other studies. For example, Hsu et al. (2022) examine that a higher number of female directors within management boards leads to better integration of ESG aspects in business operations, and Bosone et al. (2022) find a positive association between gender diversity and the share of sustainable investments within a firm. Furthermore, investments in sustainability are characterized by the fact that they do not necessarily yield short-term increases in corporate value but rather represent long-term commitments (Ferrell et al., 2016). As previous research suggests that females exhibit a greater ability and willingness to delay gratification compared to males, female analysts might be more concerned about the ESG performance of the companies they cover (Silverman, 2003). Based on this, I anticipate a positive association between an analyst’s female gender and their likelihood to ask ESG-related questions. Related research has shown that the behavior of analysts and directors in conference earnings calls aside from ESG questions is impacted by gender as well. Female analysts tend to speak with a more positive and less vague tone while asking less about numerical content (De Amicis et al., 2021; Francis et al., 2020). Female directors, in addition, are more benevolent and universally concerned than male directors (Adams and Funk, 2012). These characteristics strengthen the assumption that female analysts inquire more often about ESG during the Q&A. However, the phenomenon wherein highly qualified women choose to enter traditionally male-dominated fields such as equity research might present a contrasting perspective. Built upon a self-selection hypothesis, which posits that females employed in the financial services industry often emanate from a distinct subset of highly qualified women, it is conceivable that these individuals may not exemplify typical female personality traits (Kumar, 2010). For instance, while women in the broader population have been identified as being more supportive of sectors like education, health, and social welfare (Shapiro and Mahajan, 1986), this tendency may not necessarily extend to females employed as equity research analysts, who may exhibit behavioral patterns more akin to those of males. However, considering the previously described research indicating that female analysts place greater importance on ESG topics, I hypothesize the following concerning the relationship between gender and the propensity to ask ESG-relevant questions:

H1: Questions asked by female analysts are more often ESG-related than those of male analysts.

3.3.2 Age

I observe the factor of age, as analysts from different age groups could embrace different personal character traits, including contrasting cultural norms, habits, and life experiences. Previous research about the age of equity research analysts suggests mixed results. Although the impact of an analyst's age on their likelihood to ask ESG-related questions has not been measured yet, different studies show that age does not impact other traits relevant for analysts significantly. In the general population, literature from the field of psychology has demonstrated an increased risk aversion with advancing age (Pålsson, 1996). Considering the global threat posed by climate change and various social crises, based on this knowledge, it can be assumed that older analysts are more aware of this risk and therefore ask more ESG-related questions than younger analysts. In contrast to this, older people tend to perceive their future horizons as shrinking, which influences their decision-making, leading them to

prioritize short-term benefits and emotional well-being (Löckenhoff, 2011). Given the long-term focus of ESG-related issues, older analysts might demonstrate less interest in these topics due to their shorter perceived future time horizons. This could result in fewer inquiries about ESG matters during earnings conference calls. Furthermore, Przychodzen et al. (2016) have shown that older fund managers incorporate ESG factors less into investment decisions. As I find indicators for both a positive and a negative association, I propose the hypothesis:
H2: The age of analysts has no impact on the frequency at which they pose ESG-related questions.

3.3.3 Years of Experience

In addition to age, I examine the effect of years of experience.[2] I expect a high correlation between years of experience and age, as many analysts begin their careers in finance or switch to it soon after. The reason for studying this is that individuals who have fewer years of experience than what their age suggests might have previously gained professional experience in another industry. Since the recommendations of equity research analysts significantly influence the short-term trading of institutional investors, there could be a skewness in analysts' recommendations towards short-term gains, potentially leading to a systematic neglect of long-term company health and sustainable investment strategies (Cremers et al., 2021). Analysts with prior professional experience in other sectors might be less influenced by this tendency and therefore pose more ESG questions.
Thus, I hypothesize:
H3: More experienced analysts ask fewer ESG-related questions than less experienced analysts.

3.3.4 Recession

To measure the economic conditions under which an analyst started their career, I observe whether an analyst began their career in a finance-related position during a period of economic recession or not. There is evidence that the economic environment in which managers start their careers is important for career development as well as decision-making on a personal level. Starting a career during an economic recession is associated with persistently

[2] Experience is defined as the number of years an analyst has worked in equity research, other front-office finance roles such as investment banking or investment management, or as a journalist covering the financial market.

lower earnings and a lower return on investment in higher education (Oreopoulos et al., 2012) Furthermore, managers who begin their careers during a recession adopt a more conservative management style, leading to lower investments in capital expenditures and research and development (Schoar and Zuo, 2017). The transition of a company towards greater sustainability, however, is a long process, requiring significant capital investment and not necessarily yielding immediate monetary benefits. Against this backdrop, I assume that analysts who commenced their careers during a recession place less emphasis on ESG issues. Therefore, I propose the following hypothesis:

H4: Analysts who started their first job in the finance sector during a recession ask fewer ESG-related questions.

3.3.5 MBA and STEM Degrees

Concerning the education of analysts, I observe two particular backgrounds: whether an analyst has an undergraduate or graduate degree in a STEM subject, and whether he has an MBA. There is limited literature regarding the connection between these two backgrounds and ESG. MBA programs are generally criticized for being too focused on short-term performance while insufficiently teaching innovation and long-term wealth creation (Hambrick and Mason, 1984). Yao (2022) finds that graduates of MBA degrees where ESG courses are a mandatory part of the curriculum work in more sustainable sectors and at firms with better ESG performance. Regarding STEM backgrounds, Botsari and Lang (2020) examine that in the realm of venture capital investing, investors with a STEM degree more frequently incorporate ESG considerations into their investment decisions compared to those with a business degree. This aligns with the findings of Schumacher (2022), who also observes a stronger awareness regarding ESG matters among individuals with STEM degrees but also notes their limited representation in the finance sector. Therefore, I propose that:

H5: Analysts holding an MBA degree inquire less about ESG than those without one.

H6: Analysts with a STEM background ask more ESG-related questions compared to analysts with other educational backgrounds.

3.3.6 Network Size

In previous literature, network size is often investigated as an attribute of managers. Kirchmaier and Stathopolous (2008) find that firms managed by CEOs with a larger network size perform worse financially. In addition, a larger network is positively associated with greater firm risk, as CEOs consider a large network as career insurance, encouraging them to take greater managerial risk (Fan et al., 2021). Even though these observations have been made for managers rather than analysts, I assume a negative relationship between network size and governance issues. With respect to the impact of network size on ESG matters, several papers have shown a positive effect of network size on the incorporation of ESG-related topics into corporate decisions. Harjoto and Wang (2020) examine that larger network size of board directors increases overall ESG performance. Also, network centrality measures for board directors are positively linked to the environmental and social scores of a firm (Downing et al., 2022).[3] As there is no direct research on the connection between analysts' network size and their likelihood to ask questions related to ESG during conference calls, I assume similar effects like the ones for managers. Thus, I hypothesize:

H7: Analysts with a larger network size ask more questions related to environmental and social issues while asking less about governance.

3.3.7 Bulge Bracket, Number of Star Analysts, and Years at the Current Company

Finally, I measure the impact that the corporate culture of the company an analyst works for has on the likelihood of them asking ESG-related questions. Corporate culture may include norms, customs, and values and can therefore have a direct impact on employee behavior (Gorton et al., 2022). This can occur for two primary reasons. Firstly, companies may attract employees who identify with their corporate culture based on the nature of this culture itself. Secondly, the culture within the company can shape the mindset and actions of its employees over the long term. To gauge corporate culture, I adopt a twofold approach: examining the effect of employment at a bulge bracket bank[4] and analyzing how the number of All-American analysts[5] in the firm of an analyst impacts the frequency of ESG-related inquiries. Mainelli et al. (2009) find that traditional sell-side research, which is often conducted by bulge bracket banks, tends to focus on short-term financial forecasts and often neglects ESG factors. Furthermore, they observe that sell-side firms find it easier to write specialized ESG

[3] Centrality measures in this context are Degree and Betweenness. Degree is the sum of all board members of a firm who are also board members of another firm. Betweenness captures the importance of the firm regarding the flow of information within a network.

[4] Bulge bracket banks are the world's most renowned global full-service investment banks. Bulge brackets usually offer financing as well as advisory services on all continents. A full list of all banks that are considered bulge bracket banks in this study is given in Section 3.3.

[5] All-American analysts are nominated each year by the magazine "Institutional Investor". The rating takes into account several factors, including the accuracy of their forecasts, the profitability of their investment recommendations, and the quality and depth of their research.

research notes compared to bulge brackets integrating ESG evaluation into their mainstream reports. This favors analysts working for smaller boutique research firms to ask about ESG during earnings conference calls, as they are often more engaged in producing specialized research. For the number of All-Star Analysts, I anticipate a high correlation with bulge bracket firms, as these banks possess the largest equity research teams and, consequently, I expect them to employ the most analysts with All-Star status. I still examine this determinant following Park et al. (2022), who have identified that specifically non-All-American Analysts are better at predicting ESG-related events in their research. Building upon this, I aim to test whether this reflects on the firm culture in terms of reduced question activity about ESG topics in the Q&A sections of conference calls. Although corporate culture is already an important factor in job selection (Cable and Graham, 2000), I expect an intensified effect correlating with the length of time an analyst has been employed at a firm, as over time, an analyst increasingly integrates the firm's culture into their behavior. Therefore, I propose the following hypotheses:

H8: Analysts working for bulge bracket banks ask less about ESG-related questions compared to those working for smaller firms.

H9: The number of All-American analysts working for an analyst's firm is negatively associated with his likelihood to inquire about ESG.

H10: The effects described in H8 and H9 increase with the duration of an analyst's tenure at a firm.

4 Methods and Data

4.1 Capturing ESG-Related Questions in Conference Call Transcripts Using FinBERT

To evaluate whether analysts ask ESG-related questions in conference calls, I develop a machine-learning approach, which is based on a self-written Python code. As an input, the code takes transcripts of conference earnings calls downloaded from the Fair Disclosure Wire segment of the LexisNexis database. First, I make two lists of all participants in a given conference call sorted by whether they serve as corporate participants or as analysts.[6] I then extract the Q&A section of the conference call.[7] The Q&A section is subsequently segmented into individual lines. Individual questions are identified based on the presence of a

[6] Corporate participants were coded as those individuals who speak during the conference call and are not listed in the Conference Call Participant List.

[7] The Q&A section is defined as commencing with “Questions and Answers” and concluding with “Language: ENGLISH”.

colon. Upon detecting a colon, the algorithm bifurcates the line at the initial occurrence into two components: the speaker's identifier and the text of the question. The identifier is then cross-referenced with the initially compiled list of analysts to ascertain the full name as well as the current occupation of the individual.[8] The question text is defined as the text extending up to the next line that commences with a name.

To subsequently classify questions as related to ESG or not, I utilize FinBERT, a large language model that adapts to the language typically used in financial contexts. FinBERT works in such a way that it generates a contextualized embedding vector for all sentences of the input text, including information about the syntax and the semantic significance of each word within the sentence. Additionally, FinBERT stores data on the position and meaning of sentences within the context of neighboring sentences (Huang et al., 2023). For the purpose of ESG classification, I use FinBERT-ESG, a version of FinBERT that has been trained by the developers on 2,000 sentences from ESG reports and annual reports of various firms. Since its development, the FinBERT-ESG model has been employed in several research papers (Bitetto and Cerchiello, 2023; Campbell et al., 2023).
FinBERT-ESG accepts input paragraphs with a maximum length of up to 512 characters and classifies them as “Environmental”, “Social”, “Governance”, or as non-ESG-related. To ensure that questions exceeding 512 characters in length are fully analyzed by the algorithm, I partition the questions such that the algorithm assesses the question in segments of 512 characters each. However, to ensure accurate classification of the question's conclusion, the final segment always comprises the last 512 characters, even though some of these characters might have already been tested in the segment before. This strategy is used to mitigate the risk of the final segment being insufficiently long for precise analysis. The final classification result for a question is coded as the first occurrence of one of the three ESG categories or as not ESG-related otherwise. Examples of ESG-related questions from the investigated conference calls can be found in Appendix 1. As an output, the code generates an Excel file for every conference call, stating the name of the person who asked a question, their position, and the final classification for every question asked by analysts during the call.

[8] To mitigate the risk of non-identification due to minor variations in the spelling of names, all identifiers are standardized prior to cross-referencing by nullifying the effects of case sensitivity and asterisks.

4.2 Structuring the Experimental and Control Groups

After generating Excel output files for every call, I create an experimental group and a control group using a self-written Python code that employs a matching algorithm. Specifically, each ESG-related question is paired with a random question from the same conference call that has been classified as "None." The matching process is conducted completely at random. However, analysts who have already posed an ESG question in the same call are excluded from being matched within that same call (but not in others). This exclusion is due to the possibility that a matched non-ESG related question arose as follow-up question to the ESG-related query and would not have been asked in the absence of the ESG question. This approach is adopted as data for individual analysts must be manually collected. Since I am collecting ESG questions from conference calls of the largest 50 companies in the S&P 500 over 7 years, proceeding without a matching algorithm, and instead using a high-dimensional fixed effects model, would necessitate manually collecting data for every question of all calls.[9] This would be too time-consuming for the scope of this project. The model-based reasons for matching on an individual call level as opposed to random matching across all calls are explained in Section 5.1.

4.3 Collection of Analysts' Data

Since earnings conference call transcripts only explicitly disclose the names and current occupations of the analysts, additional sociodemographic and professional data about the analysts must be obtained from other sources. For all analysts, I collect data at the singular question level, meaning that if an analyst is represented by multiple questions in the dataset, all data for each question is collected individually. Particularly, time-variable factors such as age or years of experience can vary for the same analyst across different questions. Subsequently, the sociodemographic and professional factors that were examined in this study, along with their definitions and the methods used for their determination, are introduced.

To determine the gender of analysts, I classify first names using Gender API. Gender API is a classification algorithm that assigns a gender to a first name using data from social media platforms and other publicly available sources. This method has been frequently used in related research (Nielsen et al., 2017; Comprix et al. 2022). Using Gender API, I was able

[9] In total, there are 26,691 questions (see Section 4.4).

to identify the gender of all analysts in the dataset. I collect all other data manually using information available on LinkedIn.com, Interdependence.org, Zoominfo.com, and from the Financial Industry Regulatory Authority. For structured data collection of the other determinants, I first create an index $i = 1, \ldots, I$, which indexes each question in the dataset. I represents the total number of questions in the dataset.[10] Furthermore, I introduce A_i as the analyst asking question i.[11] To determine age, I use the following algorithm: If the year of starting an undergraduate program is known, the age of the analyst asking question i is calculated by

$$Age_{A_i} = YoCC_i - YoUE_{A_i} + 19$$

where $YoCC_i$ is the year of the conference call in which question i was asked and $YoUE_{A_i}$ is the year of university entry of the analyst who asked question i. This reflects the youngest typical enrollment age for undergraduate students in the United States (OECD, 2022).[12] If this information is not available, the age is then determined in the second step by

$$Age_{A_i} = YoCC_i - YoG_{A_i} + 23$$

where YoG_{A_i} is the year when the analyst asking question i graduated university, reflecting the average degree duration of four years in the US.[13] If there is no information available regarding the undergraduate study period but a job position can be clearly identified as an entry-level position after graduation, the age is calculated by[14]

$$Age_{A_i} = YoCC_i - YoFJ_{A_i} + 23$$

where $YoFJ_{A_i}$is the year when the analyst asking question i started an entry-level job. This follows the assumption that a job is taken up immediately after graduation. Finally, if none of the above-mentioned information is available, I determine age using the average age of MBA graduates in the US by[15]

$$Age_{A_i} = YoCC_i - YoMBA_{A_i} + 28$$

where $YoMBA_{A_i}$ represents the age of MBA graduation of the analyst asking question i. In all other cases, age is not determined. To quantify the professional experience of analysts, I

[10] This and all subsequent variables retain their meaning throughout the rest of this section.

[11] Note that for any $1 \leq m, n \leq I$, analyst A_m can be the same person as A_n. However, they are still treated separately because if, for example, the year of questions m and n is different, the age of $A_m$would be different from that of A_n.

[12] Typical enrolment ages are defined by the OECD as the age interval that covers at least 60% of students at that level, from the 20th to the 80th percentile of the enrolled population whose age is known.

[13] For analysts with a European background, an average duration of three years for a Bachelor's degree and five years for a combined Bachelor's and Master's degree program was assumed.

[14] This includes a consecutive Master's degree program for US students.

[15] Harvard Business School has reported an average of 27 for their 2020 class (MetroMBA, 2022). As the duration of the degree is 2 years, the average graduation age would therefore be 28.

sum up all periods (rounded to the nearest full year) during which an analyst has worked in the fields of investment banking, investment management, equity research, or financial journalism.[16] Therefore, I use the following approach:

$$Years\ of\ Experience_{A_i} = \left(\sum_{j=1}^{n_i - 1} FY_{A_i,j} - SY_{A_i,j} \right) + YoCC_i - SY_{A_i,n_i}$$

The index $j = 1, \dots, n_i$ indexes all periods in which the analyst who asked question i has worked in a front-office finance role in chronological order. $SY_{A_i,j}$ represents the starting year of a given period j and $FY_{A_i,j}$ the final year. Since the last period in which an analyst worked in equity research cannot be considered completed by definition, as they are still asking a question at the time of the conference call, this final period must be treated differently as $FY_{A_i,n}$ is not given. Therefore, I define $FY_{A_i,n}$ as the year where question i was raised. To gather data on whether an analyst began their career during a recession, I use data from the National Bureau of Economic Research and collect all years since 1945 during which a recession occurred, either wholly or partially, in the United States (National Bureau of Economic Research, 2023). From these years, I form a set R. Subsequently, for each question, I determine whether the analyst who asked the question started their first front-office finance role during one of these recession years. Therefore, I define:

$$Recession_{A_i} = \begin{cases} 1, & SY_{A_i,1} \in R \\ 0, & \text{else} \end{cases}$$

Analysts with an MBA are defined as those who have completed a Master of Business Administration, a non-consecutive degree program that requires prior professional experience, at a business school. I encode the possession of an MBA in a binary manner:

$$MBA_{A_i} = \begin{cases} 1, & A_i \text{ possesses an MBA} \\ 0, & \text{else} \end{cases}$$

STEM graduates are those who possess either a Bachelor's, Master's, or PhD in one of the fields typically associated with STEM.[17] I encode the possession of a STEM degree similar to MBA by

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[16] The scope considered as professional experience is narrowly defined to enable the examination of the effects described in section 2.3.3 of professional experience in distinction from age.

[17] In 2016, the work permit for graduates with a STEM degree was extended by 24 months. As a result, an increasing number of universities in the USA are seeking STEM accreditation to become more attractive to students. This has led to degrees in Business, Psychology, and other fields not traditionally associated with STEM officially receiving STEM accreditation. However, in the context of this work, only those subjects that can be directly assigned to one of the terminologies Science, Technology, Engineering, or Mathematics are considered to avoid dilution of the effect.

$$STEM_{A_i} = \begin{cases} 1, & A_i \text{ possesses a STEM degree} \\ 0, & \text{else} \end{cases}.$$

I obtain data to test network size by using the number of LinkedIn followers an analyst has. However, there is a central issue with this data, as it was collected in January 2024 and there is no information about the development of this number at earlier dates. Using only the number of LinkedIn followers could introduce a temporal bias, potentially attributing a larger network to analysts asking questions earlier in time, as the analyst might not have had a part of their 2024 network at the time of the conference call. Therefore, I apply a correction factor based on the assumption that an analyst's network has grown linearly since the start of their career. This factor adjusts the network size based on the proportion of time between the analyst's career start and the conference call relative to their entire career up to 2024. Thus:

$$Network\ Size_{A_i} = \frac{YoCC_i - SY_{A_i,1}}{2024 - SY_{A_i,1}} \cdot LF_{A_i}$$

LF_{A_i} represents the number of LinkedIn followers of the analyst asking question i. Regarding data to evaluate whether an analyst works at a bulge bracket firm, I utilize the approach of Gemici and Lai (2019), who define a list of 10 large and international investment banks, as commonly used by industry participants, as bulge bracket banks.[18] Accordingly, I use a binary variable to gain data for this determinant based on whether an analyst is employed by one of these banks using the information about the current job of an analyst given in earnings conference call transcripts:

$$Bulge\ Bracket_{A_i} = \begin{cases} 1, & F_{A_i} \in BB \\ 0, & \text{else} \end{cases}$$

Here, F_{A_i} is the firm for which the analyst asking question *i* works, and BB is a set consisting of all bulge bracket banks. For this purpose of determining the number of All-American analysts at the firm of A_i, I use data from Institutional Investor, which has been aggregated at the firm level (Bragg, 2021). Using the count function

$$SA(x, y) = \#\text{All-American analysts working for firm } x \text{ in year } y$$

I determine the number of All-American analysts by

$$Star\ Analysts_{A_i} = SA\left(F_{A_i}, YoCC_i\right)$$

Finally, I obtain the number of years an analyst has worked for his current company by

$$Years\ at\ Current\ Company_{A_i} = YoCC_i - SY_{A_i,n_i}$$

[18] These banks are J.P. Morgan, Goldman Sachs, Citi, Bank of America Merrill Lynch, Morgan Stanley, Deutsche Bank, Barclays, Credit Suisse, UBS, and HSBC.

4.4 Sample Formation

Table 1: Sample selection procedure

This table presents the sample selection process, first outlining the chosen transcripts and then detailing the selection of questions for examination.

		Transcripts available for data sourcing	
Step	Description	Addition / Reduction	Transcripts
(1)	Potential number of quarterly earnings conference call transcripts of the 50 largest companies in the S&P 500 (Q1 2015 - Q4 2021)		1,400
(2)	Firms not holding quarterly earnings conference calls	-28	1,372
(3)	Transcripts not available in the LexisNexis database	-19	1,353
(4)	Transcripts without Q&A section	-19	1,334
(5)	Final number of transcripts used for data sourcing		1334
Within the 1,334 transcripts, I identify 26,691 questions			
		Number of questions selected for the main model	
Step	Description	Addition / Reduction	Questions
(6)	Number of questions in all investigated calls		26,691
(7)	Questions not related to ESG	-26,348	343
(8)	Matched questions without ESG relevance	+326	669
(9)	Questions with incomplete data about the analyst	-152	517
(10)	**Main model**		**517**

Table 1 presents the sample selection procedure for the final dataset. I start by downloading conference earnings call transcripts of the 50 largest companies listed in the S&P 500 based on market capitalization in the time range 2015-2021 from the LexisNexis database.[19] This leads to a potential database of 1,400 earnings conference call transcripts.[20] I was able to acquire and use 1,334 of these transcripts. This reflects that only 49 of the 50 companies held quarterly earnings calls in the investigated time frame.[21] Additionally, 19 transcripts

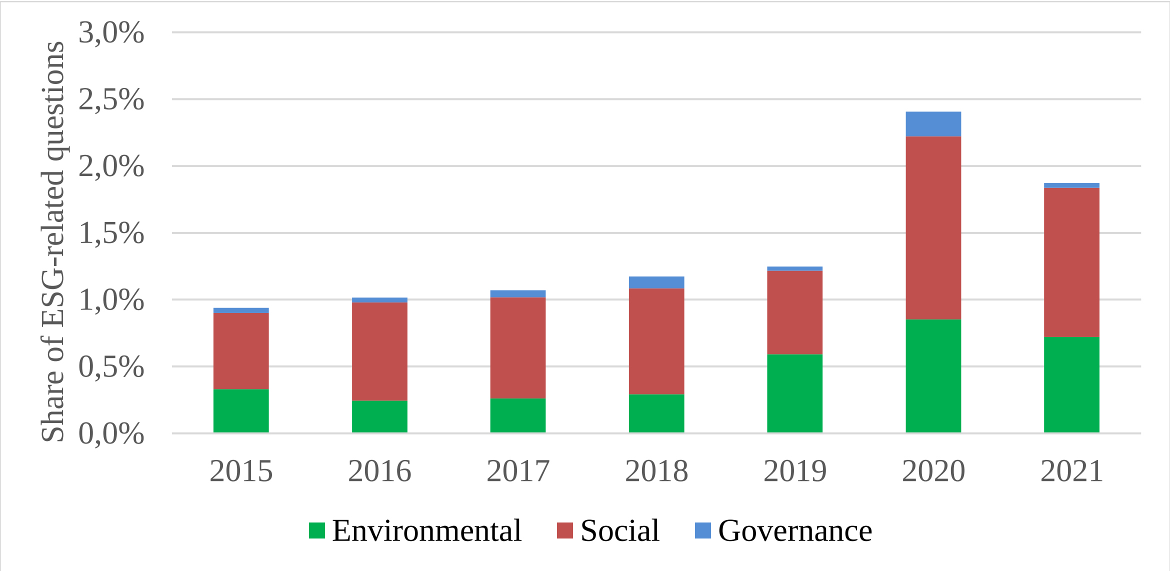
[19] As of July 1, 2023.
[20] The number 1,400 results from multiplying 50 firms, 7 years, and 4 quarters.
[21] Berkshire Hathaway Inc. is one of only a few large US companies not holding earnings conference calls. The firm's CEO Warren Buffett does not want investors to base their investment decisions on short-term trends and therefore decided to not hold conference calls between 2015 and 2021.

were not available in the database and 19 of the available transcripts did not include a Q&A section. After extracting all questions from the calls using my algorithm, I have compiled a dataset comprising a total of 26,691 questions, of which 113 are classified as "Environmental", 214 as "Social", 16 as "Governance", and 26,348 as "None". Therefore, the total number of ESG-related questions in the sample is 343, resulting in an average of 0.257 ESG-relevant questions per conference call. After matching each ESG-related question with a non-ESG-related question, the dataset for which I subsequently hand-collect sociodemographic and professional factors consists of 669 questions. This number does not correspond to a doubling of the number of ESG-related questions, as in some calls there were no analysts who did not ask any ESG questions, thus leaving no questions available for matching.[22] After collecting all data points for each analyst, as described in Section 4.3, there are 517 questions for which all data is available. These questions constitute the final dataset for the model.

4.5 Frequency of ESG-Related Questions

Figure 1: Share of ESG-Related Questions Across Time

This figure presents the yearly share of questions related to environmental, social, and governance issues out of all questions analyzed. The x-axis represents the years 2015 to 2021, while the y-axis shows the percentage share of a category among all questions posed in the respective year. The data is calculated using all 26,691 questions.



[22] An example of this can be found in the Q1 earnings conference call of Netflix Inc. In this call, there were only two analysts asking questions and both of them asked at least one ESG-related question. Therefore, there was no question left for matching.

Figure 1 illustrates the development of the proportion of ESG-related questions out of all questions asked during a specific year. In line with prior research (Konieczny and Weiß, 2023), I observe that the share has grown steadily from 2015 to 2021, approximately doubling within this timeframe and underscoring the increasing relevance of the topic. An exception is the year 2020, in which the share of ESG-related questions is almost twice as high as the previous year, with the portion of questions related to social issues increasing significantly. This can be particularly attributed to the COVID-19 pandemic, from which many social questions regarding the pandemic arose. Furthermore, the data shows that analysts have significantly raised more questions related to environmental and social topics across all years compared to those related to corporate governance.

5 Model Development

5.1 Main Model

5.1.1 Model Type

To test the ten hypotheses established, I employ a logistic regression model. The model has an analyst-question panel structure. This means that each question that was asked during one of the observed earnings conference calls serves as a unique observation. Although the focus is on identifying factors that determine the likelihood of an analyst asking ESG-related questions in the Q&A section of an earnings conference call, the model is built based on individual questions rather than aggregating questions at the analyst level. This approach is taken to account for the frequency with which an analyst poses these questions. If the analysis were conducted at the analyst level, the results might be skewed, as an analyst who asks one ESG-related question would have the same weight as one who asks several.

For the dependent variable, I use a combined ESG binary variable (*ESG*), which is set to 0 for all questions classified as "None" and 1 otherwise. In Section 5.2, I expand this approach by testing for the classifications “Environmental”, “Social”, and “Governance” separately. In previous literature on whether ESG-related topics arise during earnings conference calls, researchers frequently chose to use a continuous variable for the dependent variable, in contrast to my approach in this study. This can either be attributed to entirely different modeling approaches, such as comparing transcripts to literature that is definitively ESG-relevant. In such cases, the dependent variable might be a measure of agreement (Engle et al., 2020;

Dzielinski et al., 2022). In other cases, the continuous variable is derived from the application of another large language model, where the model provides further scores that hold more information compared to FinBERT-ESG (Li et al., 2023). An alternative continuous dependent variable in this study could be the accuracy of the prediction. Nevertheless, this approach leads to two issues. Firstly, FinBERT-ESG only provides an accuracy score for one categorical classification, which would have precluded analysis divided into the three components of ESG and would only allow testing the combined score. This becomes evident in the case of a "None" classification, where the accuracy score only indicates the likelihood of the question having no ESG relevance but does not distribute the remaining probability across the three ESG categories. Secondly, the matching process described subsequently would not have been feasible with an accuracy score, as matching inherently requires a categorical classification.

5.1.2 Data Structure

To generate a control group, I employ a matching algorithm. In this process, each question in the respective experimental group is matched with a 'None'-classified question from the same conference call. While using a fixed effects model, which would include data on all 26,691 questions, would be statistically more unbiased, the motivation for this approach stems from the necessity for manual data collection as described in Section 4. The choice of call-based matching presents both a significant advantage and disadvantage. Given that the final dataset consists of only 517 individual questions, there is a considerable risk of encountering problems with overfitting and multicollinearity. The call-based matching ensures that intra-call-specific factors influencing whether ESG-relevant questions are asked are automatically controlled for. Examples include the industry in which the company hosting the earnings conference call operates or the personal characteristics of CEOs or other management members, such as age or gender. Assuming that, within the context of the architecture of the model, these factors are indeed controlled, it becomes feasible to omit all such control variables in the final model. This advantage becomes evident, for instance, in controlling for industry fixed effects. This is typically achieved through an industry classification system introduced by Fama and French (1997) which separates companies into 48 different industries. In a model with only 517 observations, the risk of overfitting and multicollinearity would significantly increase, as 47 additional dummy variables would need to be included to control for industry fixed effects alone.

A potential disadvantage arising from the matching method is the issue of endogenous selection bias. The foundation for the correct application of matching is the premise that a matched analyst is selected randomly, and this choice is not dependent on external factors. However, since firms can influence which, when, and to what extent certain analysts are allowed to ask questions, they have the potential to disrupt this randomness based on their own agenda. Particularly when there are reasons that correlate both with the selection process and the outcome, namely whether a question related to ESG issues is asked or not, a bias arises. As described in Section 3.2, there can be various reasons why firms might wish to include or exclude ESG topics from their conference calls, which are not controlled in the model. Consequently, due to the structure of the dataset, there is a risk of endogenous selection and omitted variable bias.

5.1.3 Independent Variables

I will briefly introduce the included independent variables of the main model.[23] To test the ten hypotheses, I use ten independent variables along with two interaction terms, while controlling for year-quarter fixed effects and the word count of questions. For the gender of analysts, I include a dummy variable (*FEMALE*) indicating whether or not an analyst is female. Age (*AGE*), experience (*EXPERIENCE*), and time at the current company (*COMPYEARS*) are all modeled as continuous variables in the unit of years. To represent the economic conditions at the start of the analysts' careers, a binary variable is included, indicating whether there was a recession at the time when the analyst entered the industry (*RECESSION*). The possession of an MBA (*MBA*) as well as having a STEM degree (*STEM*) are both included as binary variables as well. Network size (*NETWORK*) is incorporated as a continuous, time-discounted variable. Finally, I employ a dummy variable (*BULGEBRACKET*) indicating whether a global investment bank employed an analyst at the time of the respective conference calls, and a continuous variable (*STAR*) which denotes the number of All-American analysts at the respective firm. Furthermore, I control for year-quarter fixed effects by including categorical variables for year and quarter. Another control variable I utilize is the word count of individual questions (*WORDCOUNT*). The length of entire Q&A

[23] If not specified otherwise, the particulars and methods of calculation for the independent variables of the model are described in Section 3.3.

sections and individual questions is often used as a control variable in related studies employing textual analysis of conference calls, in order to control for competition constraints among analysts involved in the call (Mayew et al., 2012; Chen et al., 2018; Rennekamp et al., 2022).[24]

The final main model (Model 1) has the form:

$$\ln\left(\frac{p(ESG=1)}{1-p(ESG=1)}\right) = \beta_0 + \beta_1 FEMALE + \beta_2 AGE + \beta_3 EXPERIENCE$$
$$+\beta_4 COMPYEARS + \beta_5 RECESSION + \beta_6 MBA + \beta_7 STEM + \beta_8 NETWORK$$
$$+\beta_9 BULGEBRACKET + \beta_{10} STAR + \gamma_1 WORDCOUNT + YEAR\ FE + QUARTER\ FE$$

Here, *p(ESG=1)* represents the probability determined from the model that a question is related to ESG.

5.1.4 Univariate Statistics

Table 2 presents the descriptive statistics of all independent variables in the main model, excluding categorical variables measuring year-quarter fixed effects. In the analysis, mean values and standard deviations for both groups are provided, and a two-tailed t-test is used to determine the statistical significance of the difference between them. I will summarize the main findings here and give further details in Section 5.1.

The results show that 16% of the ESG-related questions are posed by female analysts, compared to 10.2% in the control group. In line with the first hypothesis H1, it appears that female analysts are significantly (p = 0.054) more likely to ask questions on ESG topics compared to their male counterparts. Furthermore, the univariate analysis reveals that the timing of career commencement is particularly relevant for addressing ESG topics in the Q&A sections of conference calls. ESG-related questions are 9.1 percentage points less often raised by analysts who began their careers in finance during a recession. In accordance with the assumption made in hypothesis H3, this indicates that the economic conditions during the formative early years of a career have a significant influence on the questioning behavior of analysts (p = 0.005). Finally, it becomes evident that corporate culture, in the sense of working for a bulge bracket firm, also influences ESG-related questions. As hypothesized in

[24] The word count of an individual question does not provide a solid basis for inferring personal characteristics of analysts. Consequently, WORDCOUNT is included in the model as a control variable but not as a determinant to be independently investigated.

Table 2: Descriptive Statistics based on ESG-content of questions

This table compares group means and standard deviations along with the statistical significance (two-tailed t-test) of the difference for all variables of interest as defined in Section 4.3 and the wordcount for ESG-related and non-ESG-related questions. Asterisks indicate the statistical significance of the *p*-values: <0.01 (***), <0.05 (**), <0.1 (*).

	Non-ESG-related questions		ESG-related questions		Non-ESG-related vs. ESG-related questions	
	Mean	SD	Mean	SD	Diff.	*p*-value
FEMALE	0.102	0.304	0.160	0.367	-0.058	0.054*
AGE	45.071	7.296	45.555	7.186	-0.484	0.447
EXPERIENCE	16.693	6.685	17.099	7.025	-0.406	0.502
COMPYEARS	7.858	6.200	7.943	6.704	-0.085	0.882
RECESSION	0.205	0.404	0.114	0.319	0.091	0.005***
MBA	0.469	0.500	0.437	0.497	0.031	0.477
STEM	0.244	0.430	0.221	0.415	0.024	0.527
NETWORK	1973.934	9650.614	1128.759	1050.147	845.175	0.159
BULGE-BRACKET	0.429	0.496	0.357	0.480	0.072	0.095*
STAR	14.980	15.312	13.331	13.987	1.650	0.201
WORDCOUNT	60.937	35.578	44.551	39.770	16.386	0.000***

H8, analysts who work in smaller research boutiques or outside of equity research, such as on the buy-side or in journalism, are more inclined to address ESG topics in their questions. This is evidenced by the fact that 7.2 percentage points fewer of the analysts who ask such questions are employed by a bulge bracket bank (p = 0.095). From all other variables of interest, no statistical association can be detected in the univariate analysis. However, it is noteworthy that the control variable of word count has a significant influence on whether a question is ESG-related. ESG questions are on average 16.386 words shorter than non-ESG related questions (p = 0.000). Since word count can be interpreted as a measure of the competitiveness of a question, it suggests that ESG questions are asked in a less aggressive manner. Another noticeable observation in the results is the difference in the standard deviations for *NETWORK* between the two groups. Questions unrelated to ESG exhibit a standard deviation that is 9.2 times larger than that of questions with ESG relevance. This can be attributed to the presence of some analysts from the journalism sector having over 100,000 LinkedIn followers, as after winsorizing at the 1st and 99th percentiles, the standard deviation of the questions not related to ESG became even smaller than the one of ESG-related questions.[25]

5.2 Submodels

In addition to the main model, I employ four additional models, which allow for a more targeted examination of some of the proposed hypotheses. For the second model, I modify the main model in such a manner that it yields results pertaining to hypothesis H10. I employ two interaction terms between *BULGEBRACKET* and *COMPYEARS*, as well as between *STAR* and *COMPYEARS*. By incorporating these interaction terms in combination with the individual variables, it becomes possible to assess whether a longer tenure at an analyst's employer amplifies the respective corporate cultural effects. Consequently, the second model takes the form:

$$\ln\left(\frac{p(ESG=1)}{1-p(ESG=1)}\right) = \beta_0 + \beta_1 FEMALE + \beta_2 AGE + \beta_3 EXPERIENCE$$
$$+\beta_4 COMPYEARS + \beta_5 RECESSION + \beta_6 MBA + \beta_7 STEM + \beta_8 NETWORK$$
$$+\beta_9 BULGEBRACKET + \beta_{10} STAR + \beta_{11} BULGEBRACKET * COMPYEARS$$
$$+\beta_{12} STAR * COMPYEARS + \gamma_1 WORDCOUNT + YEAR\ FE + QUARTER\ FE$$

For the third, fourth, and fifth model, instead of using *ESG* as the dependent variable, the three subcategories of ESG are tested. Consequently, the dependent variables become *ENVIRONMENTAL* (Model 3), *SOCIAL* (Model 4), and *GOVERNANCE* (Model 5). The independent variables in the third and fourth model are identical to those in the main model. However, there is a difference in the fifth model. Given that the number of questions classified as 'Governance' in the dataset is limited, I only include the independent variables of

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[25] After winsorizing at the 1st and 99th percentile, NETWORK has a standard deviation of 853.575 for Non-ESG-related questions and 951.707 for ESG-related questions.

interest.[26] Thus, the model is structured without control variables. Additionally, COMPYEARS is not included, as no specific hypothesis related to it was formulated outside of H10. The purpose of reducing the model is to preserve as many degrees of freedom as possible to enhance the quality of the results for the remaining variables. Despite these modifications, I expect the results of Model 5 to be of limited significance.

6 Results

Table 3: Determinants of ESG-related questions

This table presents the results of the five introduced models. For each variable, the logit coefficients are given, followed by the resulting odds ratios,[27] and in parentheses, the statistical significance is expressed using the *p*-value. Asterisks indicate the statistical significance of the *p*-values: <0.01 (***), <0.05 (**), <0.1 (*).

Dependent variable	ESG		ENVIRONMENTAL	SOCIAL	GOVERNANCE
Model No.	(1)	(2)	(3)	(4)	(5)
FEMALE	0.723**	0.731**	0.553	0.694*	-5.614
	2.061**	2.078**	1.739	2.001*	0.004
	(0.014)	(0.013)	(0.328)	(0.072)	(0.316)
AGE	0.011	0.011	0.055	0.012	-0.087
	1.011	1.011	1.057	1.012	0.917
	(0.565)	(0.564)	(0.171)	(0.625)	(0.769)
EXPERIENCE	-0.001	0.001	-0.108**	0.022	-0.525
	0.999	1.001	0.898**	1.022	0.592
	(0.972)	(0.974)	(0.025)	(0.399)	(0.437)
COMPYEARS	-0.002	-0.025	0.078**	-0.020	
	0.998	0.975	1.081**	0.080	
	(0.920)	(0.259)	(0.018)	(0.336)	

[26] In the dataset, a total of 16 questions are classified as 'Governance'. Among these questions, complete information about the analyst is available for only 8 questions.

[27] In logistic regression models, the interpretation of coefficients is less intuitive compared to ordinary least squares models. However, the interpretation can be simplified by providing the odds ratios. An odds ratio (O) for an independent variable can be derived from the logit coefficient (β) through the formula $O = e^{\beta}$, where e is the base of the natural logarithm. In a logistic regression model with multiple independent variables, the odds ratio for a specific variable gives a factor of how the odds of the dependent variable being equal to one change with a one-unit increase in the independent variable, while holding all other variables constant. It is important to mention that the odds do not correspond to the probability of an event but can be expressed, given that P represents the probability that the dependent variable is 1, as: $Odds = P/(1-P)$. Thus, a change in the odds is different from a change in probability.

RECESSION	-0.817***	-0.799***	-0.886	-0.702**	-3.710
	0.442***	0.450***	0.412	0.496**	0.024
	(0.002)	(0.003)	(0.118)	(0.047)	(0.178)
MBA	-0.155	-0.156	-0.823**	-0.025	0.219
	0.856	0.855	0.440**	0.975	1.245
	(0.445)	(0.444)	(0.038)	(0.925)	(0.930)
STEM	0.068	0.098	1.012**	-0.425	-3.039
	1.070	1.103	2.752**	0.654	0.048
	(0.781)	(0.690)	(0.025)	(0.206)	(0.578)
NETWORK	0.000	0.000	0.000	0.000	0.002
	1.000	1.000	1.000	1.000	1.002
	(0.297)	(0.334)	(0.460)	(0.350)	(0.375)
BULGE-BRACKET	-0.539**	-0.614**	-1.070**	-0.638*	13.210
	0.584**	0.541**	0.343**	0.528*	545,711.700
	(0.040)	(0.015)	(0.040)	(0.071)	(0.236)
STAR	0.006	-0.008	0.041**	0.003	-0.394
	1.006	0.993	1.042**	1.003	0.675
	(0.492)	(0.628)	(0.026)	(0.791)	(0.198)
BULGE-BRACKET * COMPYEARS		0.010			
		1.010			
		(0.811)			
STAR * COMPYEARS		0.001			
		1.001			
		(0.317)			
WORD-COUNT	-0.013***	-0.013***	-0.009	-0.015***	
	0.987***	0.988***	0.991	0.985***	
	(0.000)	(0.000)	(0.105)	(0.000)	
Constant	0.617	0.742	-0.079	0.680	11.187
	1.854	2.100	0.924	1.974	72,201.270
	(0.409)	(0.325)	(0.957)	(0.489)	(0.332)
Year FE	YES	YES	YES	YES	NO
Quarter FE	YES	YES	YES	YES	NO
Observations	517	517	177	321	21
Pseudo *R*-squared	0.069	0.072	0.139	0.109	0.518

To test whether the results of the univariate statistics hold, I perform multivariate tests using the models introduced in Section 5. The results of the five models are presented in Table 3. Initially, I will explain some of the observations regarding the results at the model level and then proceed to analyze the outcomes for the individual hypotheses.

The first four models demonstrate that there exist specific sociodemographic and professional determinants which significantly influence the extent to which analysts address ESG topics in their inquiries during earnings conference calls.[28] Contrastingly, the coefficients of Model 5 differ markedly from those of the other models and do not exhibit any statistically significant relationships. Consequently, due to the limited data set and resultant overfitting, the outcomes of this model do not permit the drawing of meaningful conclusions.[29] Among the other four models, there are differences in both the signs of the logit coefficients for the same independent variable[30] and in the number of statistically significant relationships between the dependent and independent variables. It is particularly noteworthy that the determinants which significantly influence the posing of questions in the categories of environmental and social differ considerably. Among the independent variables of interest, six show a significant relationship with the dependent variable *ENVIRONMENTAL*, and three with *SOCIA*L, with only one having a significant association with both. The significant coefficients in the main model match those in Model 4, implying conversely that none of the coefficients that are significant in Model 3 but not in Model 4 are significant in the aggregated view of the main model. Therefore, the chosen approach of dividing the analysis into the three subcategories of ESG, in addition to the main model, is validated as this approach reveals that the important factors for asking environmental-related questions differ from those for social-related ones.

[28] The Pseudo *R*-squared value of the main model, at 0.069, is slightly lower but within a similar range as the Adjusted R-squared of 0.095 in the study by Li et al. (2023), which is the only one exploring a similar research question. However, comparing these studies is challenging due to significant differences: Firstly, the type of model used (Li et al. (2023) employed Ordinary Least Squares (OLS) rather than logistic regression), and secondly, the differences in independent variables in the models, as this study incorporates a more extensive range of variables of interest while having fewer control variables.

[29] Another way to analyze the significance of entire models is through the *p*-value for the model's chi-squared test of overall significance. This test assesses the null hypothesis that all of the regression coefficients (other than the constant term) are zero. The resulting values are 0.000 for Models 1, 2, and 4, 0.026 for Model 3, and 0.107 for Model 5. This indicates that Models 1-4 are significant at the 5% level, while Model 5 remains insignificant even at the 10% level.

[30] As an example, COMPYEARS is positively associated with ENVIRONMENTAL and negatively associated with SOCIAL.

My findings confirm hypothesis H1. As expected from the results of Li et al. (2023), I find that female analysts ask significantly more ESG-related questions compared to male analysts. When a random question is asked by a female analyst, the odds of the question being ESG-related increase by 106.1% (*p*=0.014). This odds ratio is large and economically meaningful. However, this significant correlation exists only for questions related to social issues in the submodels. Therefore, the positive correlation between female directors and sustainable operations and investments within companies (Bosone et al., 2022; Hsu et al., 2022) is not reflected in the tendency of female analysts to inquire more frequently about environmental topics. Furthermore, the findings do not support the self-selection hypothesis (Kumar, 2010). Based on the results, female analysts, at least in the dimension of asking ESG-related questions, appear to conform more to the characteristics traditionally attributed to women in sociological literature.

The models provide no evidence of an impact of age on the addressing of ESG topics. While the coefficients are positive across all models, none of them are significant. Therefore, hypothesis H2 holds.

From the main model, no results emerge that support the hypothesis that I posited in H3. In the second model, I even observe a sign change in the coefficient compared to the main model, and both coefficients exhibit a high degree of uncertainty (*p*=0.972 in Model 1 and *p*=0.974 in Model 2). In contrast, Model 3, which is restricted to questions classified as 'Environmental', shows evidence for the assumption made in H3. For each additional year of experience, the odds that a question relates to environmental topics decrease by 10.2% (*p*=0.025). Professional experience outside the finance sector, which is examined as an additional variable to *AGE* under *EXPERIENCE* (see Section 3.3.3), thus promotes the asking of questions about environmental topics but not about other ESG dimensions.

In addition to the study by Davis et al. (2015) concerning the tone of analysts in conference calls, my model provides further evidence that beginning a career during a recession significantly influences analysts' behavior in earnings conference calls. The odds of asking an ESG-related question decrease by 55.8% (p=0.002) for those analysts who started their careers in a recession. While the coefficient is significant in the submodels only for *SOCIAL* as the dependent variable, it can be assumed that this is not the case for *ENVIRONMENTAL* solely due to the small size of the dataset. This is because the absolute value of the coefficient is even slightly higher for *ENVIRONMENTAL* compared to *SOCIAL*, and the *p*-value is just above the 10% significance level threshold (*p*=0.118). Consequently, hypothesis H4 can be accepted.

Regarding the influence of university degrees, I find mixed results. Analysts with an MBA ask fewer ESG-related questions overall and in the subcategories, although this is only significant in Model 3 (*p*=0.038). In this model, a notably pronounced effect can be observed, as when an analyst who poses a question holds an MBA degree, the odds of that question having an environmental reference decrease by 56%. Therefore, the results partially confirm hypothesis H5 and support research that identifies a strong focus on short-term performance among MBA graduates (Hambrick and Mason, 1984). For analysts with a STEM degree, the findings present an inconsistent picture. The statistically insignificant coefficient (*p*=0.781) in the main model for this determinant arises because, in Models 3 and 4, the coefficient has different signs (coef.: 1.012 in Model 3; -0.425 in Model 4), with the coefficient in Model 3 being significant (*p*=0.025). While the findings are insufficient to accept hypothesis H6, as analysts with STEM degrees inquire less about social issues, the study is in line with the results of Garibay (2015), who identified a significant negative relationship between studying a STEM discipline and social agency outcomes.

For network size, and consequently for hypothesis H7, none of the models provide statistically or economically significant evidence of an association with the posing of ESG-related questions.

Finally, the results show that the company for which an analyst works has a substantial influence on their questioning behavior. In alignment with hypothesis H8, it has been observed that analysts employed by bulge bracket banks ask significantly fewer ESG-related questions, and this factor remains the only one to exhibit statistically significant coefficients across all submodels. In the main model, the odds of a question being related to ESG decrease by 41.6% (*p*=0.040) when the analyst posing the question is employed by one of the 10 bulge bracket banks. For H10, there is no significant association concerning bulge brackets. In fact, the coefficient of *BULGEBRACKET*COMPYEARS* in Model 2 even has the opposite sign to what was hypothesized (coef.: 0.010 with *p*=0.811). Consequently, it emerges from the results that the internal effects by which a bank's corporate culture shapes its analysts' behavior during Q&A section of conference calls over the long term do not outweigh the attractive forces that an existing corporate culture exerts on analysts in job search who share similar values. The corporate cultural influence of the number of star analysts in a firm is less relevant than whether an analyst works for a bulge bracket, as a significant coefficient is found only in Model 3.[31] In this model, however, it is observed that for each All-American analyst working for the same firm as the analyst in question, the odds that a question posed by them addresses environmental topics increase by 4.2% (p=0.026). Therefore, the correlation identified by Park et al. (2022), that analysts without All-American status better predict ESG-relevant events, does not extend to the observation that firms with fewer analysts holding this status discuss ESG more in conference calls. Thus, I find no evidence supporting hypothesis H9. Similar to *BULGEBRACKET*COMPYEARS*, no significant relationship emerges for the interaction term *STAR*COMPYEARS* (coef.: 0.001; p=0.317). Although the coefficient in Model 2 has the same sign as the coefficient of *STAR*, it is also economically insignificant and thus does not support the assumption made in hypothesis H10.

Overall, the findings that were already significant in the univariate statistics are also reflected in the final results. However, by combining factors in a multivariate model and breaking the model down into subcategories, additional relationships emerge for variables that have been insignificant before, which provide evidence for many of the hypotheses established.

7 Limitations

This study has five limitations that open up opportunities for further research. Firstly, despite choosing FinBERT-ESG, a natural language processing method trained to identify ESG themes in financial discourse, during the data collection phase, some inaccuracies become

[31] It should be noted that, as expected, there is a high correlation between *BULGEBRACKET* and *STAR* (coef.: 0.6074) in the entire dataset. Therefore, the additional inclusion of *STAR* in the model provides little further explanation for the variance of the dependent variable. To be able to examine the effect of *STAR* separately, I have implemented an additional model that mirrors the main model but omits the *BULGEBRACKET* variable. However, no significant result emerges for the coefficient of *STAR* (coeff.: -0.006 and p=0.388) in this case as well.

apparent in its application. In particular I observe many false positives in the dataset, especially with short questions classified as “Social”.[32] An algorithm specifically trained on conference call transcripts and with a larger training data base than 2,000 sentences might achieve more accurate results. Furthermore, there is an issue with some questions being cut off by the algorithm before they actually ended despite the use of some safeguards in the code. Most of these cases occur if the transcript has an unusual formatting like a line break at that point.[33] Another limitation arises from the design of the study, which requires manual data collection. With a larger research team or a database that gathers the examined data for analysts, it would be possible to forego the matching algorithm and instead apply a fixed effects model. Therefore, the models would benefit from a larger data base, enhancing the statistical significance of the sub-models, which currently suffer from a limited number of observations. Additionally, it would reduce the risk of bias due to endogenous selection. Within the current matching algorithm there is another limitation arising from the fact that the matching algorithm is applied before data about the observations is collected. Subsequently, some of the matched observations are not part of the final model in cases where some data is unavailable. Therefore, there is a skewness in the control of intra-call fixed effects (see Section 5.2). A third limitation arises from the quality of data or the absence of specific data. The data collected for the study is based on assumptions for calculating individual factors (see Section 4.3), resulting in the values used being partially inaccurate by default. Factors such as network size are also difficult to determine and could therefore only be included as an approximation in this study.

8 Conclusion

This study provides evidence that there are sociodemographic and professional factors of analysts that are significantly associated with whether an analyst poses ESG-related questions in earnings conference calls. When categorizing questions on an aggregate basis as either ESG or non-ESG, I find that female analysts ask ESG-related questions more frequently, whereas analysts who began their careers in finance during a recession and analysts

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[32] A common example involves questions where members of the management are greeted or congratulated which are classified as ‘Social’ by the algorithm. An illustrative example of this is the statement " Congratulations to you and your team and employees.", which James Dickey Suva from Citi made during the Q1 2021 conference call of Apple Inc.

[33] I observe this particularly often in transcripts from the years 2015 and 2016, which more frequently exhibit major formatting inconsistencies.

working for a bulge bracket bank are less likely to incorporate ESG topics into their questions. Moreover, the results show that there are differences in the relevant factors across the various dimensions of ESG. Questions with a social background, which also constitute the majority of ESG questions in the dataset, exhibit the same significant relationships as observed in the aggregated analysis. For questions with environmental content, it is found that the duration an analyst has worked for their firm, having a STEM degree, and the number of All-American analysts working at the analyst's firm are positively related to the likelihood of posing ESG questions. Conversely, a negative association can be observed for the number of years of professional experience, possessing an MBA degree, and working in a bulge bracket bank. I do not obtain a significant model and subsequent results for questions on the topic of governance due to an insufficient number of observations.

Due to the continuously increasing demand from investors for ESG disclosure (Ilhan et al., 2023), it is important for research firms such as investment banks as well as public companies that host earnings conference calls to take measures to meet this demand. Given that the results of this study particularly highlight that underrepresented groups among analysts, such as women[34] or STEM graduates[35], ask significantly more questions about ESG topics, it may be important to implement further measures to increase diversity and thus the proportion of such groups among research analysts. The results also show that analysts working for bulge bracket banks, which are among the largest and most relevant banks in equity research, inquire significantly less about ESG matters in all models compared to analysts from smaller research boutiques. This indicates that corporate culture and business orientation at these firms may need to be reviewed to meet the requirements of modern equity research, which includes an analysis of ESG risks.

[34] Among all analysts for whom gender data is available in the dataset (including those not included in the main model due to the unavailability of other data), 11.5% are women.

[35] Analysts with a STEM degree constitute 23.9% of the total dataset.

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Appendix 1: Examples of ESG-Related Questions

This table presents examples of questions classified by the algorithm as "Environmental," "Social," or "Governance."

Example for a question classified as “Environmental”	The question was asked by Stephen Calder Byrd from Morgan Stanley on the Q1 2020 earnings conference call of Nextera Energy Inc and Nextera Energy Partners LP. I wanted to see if you had a strong view on the potential for further federal support for clean energy. I'm thinking just more broadly as part of the stimulus efforts that are underway. Do you see anything that might translate into concrete additional support?
Example for a question classified as “Social”	The question was asked by Nancy Bush from NAB Research on the Q3 2015 earnings conference call of Wells Fargo & Co. If you guys could just clarify, are you going to be moving people? How is this physically going to work?
Example for a question classified as “Governance”	The question was asked by Benjamin Joseph Kallo from Robert W. Baird on the Q1 2020 earnings conference call of Tesla Inc. Yes. I was asking about Mr. Mizuno entering the Board and kind of the process behind that and what he brings to the Board.

Appendix 2: Statutory Declaration

Hiermit versichere ich an Eides statt, dass ich die vorliegende Arbeit im Bachelorstudiengang Wirtschaftsmathematik selbstständig verfasst und keine anderen als die angegebenen Hilfsmittel – insbesondere keine im Quellenverzeichnis nicht benannten Internet-Quellen – benutzt habe. Alle Stellen, die wörtlich oder sinngemäß aus Veröffentlichungen entnommen wurden, sind als solche kenntlich gemacht. Ich versichere weiterhin, dass ich die Arbeit vorher nicht in einem anderen Prüfungsverfahren eingereicht habe.

Hamburg, 07. Februar 2024 Leander von Schönfeld

Ort, Datum Unterschrift (Vor- und Nachname)