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Navigating transparency: The interplay of ESG disclosure and voluntary earnings guidance☆

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ABSTRACT

In accordance with stakeholders' theory and the reputation-building hypothesis, environmental, social and governance (ESG) disclosure and voluntary earnings guidance are important ways of enhancing a firm's transparency. Using data of U.S. publicly listed companies from 2002 to 2021, we find that the level of ESG disclosure (measured with Bloomberg and machine learning (ML) ESG disclosure scores) is associated with increased information asymmetry. A subsequent examination reveals a positive relation between ESG disclosure levels and earnings guidance. The result holds in a robustness test of quasi-exogenous event of the initiation of the Bloomberg ESG disclosure coverage of firms. We deduce that firms are using voluntary earnings guidance to counterbalance the adverse impact of ESG disclosure on transparency. The study provides new insights on the factors that determine voluntary earnings guidance through firms' involvement in ESG disclosure.

1. Introduction

A heated debate has been going on regarding the importance of voluntary earnings guidance that represents a voluntary disclosure through which managers provide forecasts of their firms' forthcoming performance and communicate their own beliefs about future earnings (Call et al., 2024; Chen et al., 2011; Palmon et al., 2023). One camp argues that such guidance creates myopic behavior focused on meeting earnings growth targets, sometimes at the expense of real growth and mispricing of stocks (Berkshire Hathaway, 2000), and the other camp defends the practice as an effective tool for minimizing information asymmetry and helping align stock prices to their fundamental value (García Osma et al., 2023; Lev, 2011; Ruan et al., 2024). A more recent focus of discussion in the markets is on the importance of a company's involvement in environmental, social, and governance (ESG) disclosure (or corporate social responsibility, CSR, often used interchangeably with ESG), with the Securities and Exchange Commission (SEC) working on several proposals to govern ESG disclosure practices.[1] Although the two of these types of voluntary disclosure may seem independent, they are related through their effect on information asymmetry, as we argue in this study.[2]

Existing literature suggests that ESG performance (Cho et al., 2013; Cui et al., 2018) and earnings guidance (Diamond & Verrecchia, 1991; Verrecchia, 2001) are important sources of information that lead to a decrease in information asymmetry through a lower probability of earnings management and earnings restatements, lower bid-ask spreads,

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[1] See, for example, "Public Input Welcomed on Climate Change Disclosures" (2021), available at https://www.sec.gov/news/public-statement/lee-climate-change-disclosures ("Climate RFI"); and "Statement on ESG Disclosures Proposal" (2022), available at https://www.sec.gov/news/statement/gensler-statement-esg-disclosures-proposal-052522.

[2] In the US, ESG disclosure is still voluntary, while in Europe following the EU's Corporate Sustainability Reporting Directive (CSRD) the first tranche of mandatory ESG reports from large publicly listed companies is due in 2025.

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and lower litigation risk. Positive ESG performance may improve a company's value creation (El Ghoul et al., 2017; Li et al., 2018; Wang et al., 2023), financial performance (Li et al., 2018), and competitive advantage (Russo & Fouts, 1997); lead to a lower cost of debt (Eliwa et al., 2021; Lian et al., 2023); inhibit managerial myopia (Zhang et al., 2023); and help establish long-term relationships with key corporate stakeholders (Donaldson & Preston, 1995; Freeman, 1984). Some studies claim that ESG disclosure is closely linked to ESG performance (e.g., Bilyay-Erdogan, 2022; Brooks & Oikonomou, 2018; Cho et al., 2013; Cui et al., 2018; Tsang et al., 2023), suggesting the ESG disclosure effect on information asymmetry should also be negative. However, several recent papers have demonstrated high disagreement among existing ESG rankings (e.g., Berg et al., 2022; Christensen et al., 2022; Kimbrough et al., 2022; Serafeim & Yoon, 2022). As a result, ESG disclosure practices might lead to an increase in information asymmetry due to a lack of shared understanding of ESG metrics and their interpretation (Christensen et al., 2022; Kimbrough et al., 2022).

A firm's management can also use earnings guidance as a way of decreasing information asymmetry (Diamond & Verrecchia, 1991; Verrecchia, 2001). While several studies identify the benefits of issuing voluntary earnings guidance, such as improvement in analyst forecast accuracy (Waymire, 1986), reduction of litigation risk (Kasznik, 1999; Skinner, 1997), a lower bid-ask spread (Coller & Yohn, 1997), and a decrease in the probability of earnings management (Call et al., 2014; García Osma et al., 2023), others highlight the potential costs of issuing guidance. For example, earnings guidance may expose firms to new sources of legal liabilities (Kasznik, 1999), create proprietary costs if guidance is useful to competitors (Verrecchia, 1983), and may distract the management of the company by taking time that could otherwise be devoted to running the business (Hutton & Weber, 2001). Therefore, companies compare the benefits and costs when deciding whether to issue voluntary earnings guidance (e.g., Call et al., 2024; Feng & Koch, 2010; Krishnan et al., 2012). If a firm faces high information asymmetry, partly due to hard-to-interpret ESG disclosure, then voluntary ESG disclosure can positively relate to the likelihood of earnings guidance, as earnings guidance, despite the costs associated with the disclosure, will be the tool used for improving a firm's transparency.

While earnings guidance and ESG disclosure are different in nature, i.e., earnings guidance is a voluntary early release of mandatory earnings numbers and ESG disclosure is a voluntary release of information about ESG activities, previous research suggests that both should positively influence a firm's information transparency. Thus, since both target information asymmetry reduction, even if ESG disclosure is more multipurpose than earnings guidance, ESG disclosure can be viewed as a substitute for earnings guidance and have a negative relation with the likelihood and quality of earnings guidance. However, given their different nature and existing disagreement about disclosed ESG information, ESG disclosure and earnings guidance can be different tools used by firm management for information dissemination. Thus, it is an empirical question whether ESG disclosure is related to earnings guidance, and, if yes, in what direction.

In this paper, we examine the relation between a firm's ESG disclosure and information asymmetry, and, further, the likelihood and informativeness of voluntary earnings guidance issued by a firm's management. Specifically, we examine whether companies associated with higher ESG disclosure are less or more likely to issue voluntary earnings guidance due to effects on information asymmetry arising from ESG disclosure.

We analyze a U.S. sample of 54,878 firm-quarter observations for 2002–2021. Using regression estimations, we find a positive relation between ESG disclosure (measured with Bloomberg and machine learning (ML) ESG disclosure scores) and information asymmetry (measured with four proxies of information asymmetry: bid-ask spread, Amihud illiquidity measure, distribution of analysts' forecast and standard deviation of earnings announcements' returns). The result is opposite to theoretical assumptions made in previous studies regarding a negative relation between ESG disclosure and information asymmetry (Cho et al., 2013; Cui et al., 2018). We explain this result by building on a number of previous papers stating that information disclosed about ESG is hard to assess and judge (e.g., Berg et al., 2022; Christensen et al., 2022; Kimbrough et al., 2022), leading to an increase in information asymmetry. We further find that more ESG disclosure is positively related to the probability and informativeness of earnings guidance. This finding suggests that firm management uses earnings guidance as a traditional information release tool to mitigate the adverse effects of ESG disclosure on firm transparency. In other words, due to difficulties in understanding disclosed information about ESG, firms with higher ESG disclosure issue voluntary earnings guidance to improve transparency and overcome the problem of increased information asymmetry. We also observe positive associations between each pillar of ESG disclosure (environmental (E), social (S), and governance (G)) and the likelihood of issuing voluntary earnings guidance.

Additionally, we examine the effects of ESG disclosure on the market's response to earnings guidance, using the cumulative abnormal returns (CAR) over the three, eleven and twenty one days around company-issued guidance (CAR(−1, +1), CAR(−5,+5), CAR (−10,+10)), separately for positive, negative, and neutral or confirming guidance. The level of ESG disclosure does not have a clear significant effect on the market's response to positive guidance across both measures of ESG disclosure. The machine learning E and G scores positively relate to the CARs around confirming guidance. The results indicate that the market does not have a clear view of how to interpret information about ESG disclosure in relation to earnings guidance informativeness.

Our contribution to the literature is fourfold. First, by analyzing two measures of ESG disclosure, we contribute to previous research on the relation between a firm's ESG practices and information asymmetry (Bilyay-Erdogan, 2022; Cho et al., 2013; Cui et al., 2018). Cho et al. (2013) assume that CSR performance is also a proxy for disclosure of the underlying CSR information as CSR performance is a primary source of the information for voluntary disclosures. The authors find that higher CSR performance scores are associated with a lower bid-ask spread – the authors' measure of information asymmetry. However, they conclude without empirical testing that ESG disclosure scores should also lead to a decrease in information asymmetry in the market. To the best of our knowledge, our paper is the first to empirically test the influence of ESG disclosure on information asymmetry.

Second, by analyzing the relation between ESG disclosure and earnings guidance, we contribute to the literature that examines the determinants of voluntary earnings guidance (e.g., Diamond & Verrecchia, 1991; Verrecchia, 2001). We observe that companies that are engaged in higher ESG disclosure are associated with a higher likelihood of issuing earnings guidance, and this guidance is more informative. An increased ESG disclosure is associated with higher disagreement and a lack of shared understanding (Christensen et al., 2022; Kimbrough et al., 2022) and higher information asymmetry, confirmed by this study. Therefore, managers use voluntary earnings guidance as a tool to improve transparency and mitigate the information asymmetry problem arising from ESG disclosure.

Third, there is a prevailing sentiment among academics and practitioners that a notable disparity exists in the ESG scores, even in those issued by esteemed rating agencies (Berg et al., 2022; Christensen et al., 2022; Serafeim & Yoon, 2022; Toplensky, 2022). Therefore, we use two proxies to capture a firm's ESG disclosure: the Bloomberg ESG disclosure score and a machine learning based ESG disclosure score calculated from companies' annual 10-K reports. Our machine learning approach, namely, a word embedding model, is an important contribution in this study. We apply the technique to measure the quantity of ESG disclosure in firms' 10-K forms. Drawing insight from Li et al. (2021) allows us to come up with an approach that quantifies ESG words' semantics and represents words in the way in which humans understand words. We use this approach because Kimbrough et al. (2022) claim that ESG disclosures provided *directly* by management can resolve ESG disagreements

regarding ESG scores calculated by third parties, such as Bloomberg.

Finally, following previous studies' claims that the decomposition of ESG measures into their pillars – environmental, social, and governance – provides richer understanding of the effects of ESG practices on market participants' behavior (e.g., Baldini et al., 2018; Christensen et al., 2022; Li et al., 2018), we investigate the effects of each ESG pillar (related to ESG disclosure) on a firm's information asymmetry and the likelihood and informativeness of earnings guidance. In a more general way, our study contributes to the research that analyzes involvement in ESG disclosure to understand its relation with other important organizational and market outcomes (Christensen et al., 2022; Khan et al., 2016).

The remainder of the paper is organized as follows: Section 2 develops a conceptual framework and testable hypotheses. Section 3 describes the sample and the construction of the variables. Section 4 explains the empirical setting and the results. Section 5 concludes.

2. ESG disclosure and voluntary earnings guidance

2.1. ESG disclosure and information asymmetry

Previous research has extensively analyzed the benefits of engagement in ESG practices. Despite the growing number of papers on firms' ESG performance, evidence for its role on a firm's information asymmetry is scant (e.g., Bilyay-Erdogan, 2022; Cho et al., 2013; Cui et al., 2018). Although there is no uniform approach to determining the association between involvement in ESG activities and information asymmetry, we build our assumption on the rationale of stakeholders' theory as it is the most common theory to explain ESG disclosure (Tsang et al., 2023).

In line with stakeholders' theory and the reputation-building hypothesis, managers tend to develop relationships with different stakeholders to create a more transparent image and gain a competitive advantage over others (Freeman, 1984). Previous research claims that involvement in ESG activities plays an important role in the decision-making process of investors (Cohen et al., 2011; Brooks & Oikonomou, 2018; Ruan et al., 2024; Wan et al., 2024) and improves a firm's reputation and transparency (Tsang et al., 2023; Zhang et al., 2023). Therefore, by behaving in a socially responsible way and revealing voluntary non-financial disclosure to stakeholders, management has an opportunity to lower or mitigate the information asymmetry problem (Bilyay-Erdogan, 2022; Cho et al., 2013; Cui et al., 2018; García-Sánchez & Noguera-Gámez, 2017; He et al., 2024) due to improved corporate transparency (Cho et al., 2013; Cui et al., 2018; Dhaliwal et al., 2011), analyst forecast accuracy (Bernardi & Stark, 2018; Ruan et al., 2024), enhanced investors' confidence, and increased capital markets integrity (Martínez-Ferrero et al., 2016). Dhaliwal et al. (2012) analyze the impact of CSR disclosure on analyst forecast accuracy and conclude that companies issuing CSR reports have fewer errors in analysts' forecasts. Bilyay-Erdogan (2022) empirically confirms in the sample of 21 countries that ESG performance, as well as its three pillars – environmental, social and governance – lead to the reduction of information asymmetry surrounding the firm. Firms' engagement in ESG practices can be considered as a tool to improve communication and reduce conflicts between management and stakeholders (Bilyay-Erdogan, 2022; Tsang et al., 2023). Therefore, in line with the reputation-building hypothesis, socially responsible companies are associated with a better information environment (Kim et al., 2012) that helps reduce information asymmetry between the firm and stakeholders (Cho et al., 2013; Cui et al., 2018).

Previous research confirms that companies involved in ESG practices also tend to have higher voluntary disclosure of these activities (e.g., Bilyay-Erdogan, 2022; Dhaliwal et al., 2011). High ESG performers signal their quality to the market to positively influence their performance and future expectations (Lys et al., 2015). In the test of ESG performance on information asymmetry, Cho et al. (2013) assume that there is a close connection between ESG performance and ESG disclosure, i.e., the latter should influence information asymmetry in the same way as ESG performance, thus leading to a decrease in information asymmetry. Their assumptions are also based on the results obtained in equity and debt markets that a firm's voluntary disclosure leads to a decrease in disagreement in volatility forecasts (Lang & Lundholm, 1996), reduction in uncertainty regarding forecasted earnings (Hope, 2003), and a decrease in credit ratings dispersion (Akins, 2018), therefore mitigating the information asymmetry problem in the market (see Healy and Palepu (2001) for a review).

Building on Christensen et al. (2022), we anticipate that in contrast to financial disclosures that enjoy widespread agreement about the meaning of specific financial variables, such as leverage and profitability, ESG metrics may lack shared understanding of ESG information interpretation among market participants. As progressively more companies include ESG aspects in their reporting, it is not easy for stakeholders to recognize whether the ESG information disclosed by companies is related to ESG performance or is merely “cheap talk” (Delmas & Burbano, 2011). Stakeholders and third parties need to evaluate whether the information disclosed means a good or bad performance (Christensen et al., 2022; Kimbrough et al., 2022; Serafeim & Yoon, 2022). These difficulties with processing information from ESG disclosures and rankings do not help improve a firm's transparency, leading to an increase in subjective assessment, further disagreement, and an increase in information asymmetry.

The opposing outcomes of the above arguments suggest that the nature of the relation between ESG disclosure and information asymmetry is an empirical question with two possible outcomes. Thus, our first hypothesis stated in the null form is:

H1null. A firm's ESG disclosure has no relation with the firm's information asymmetry.

Our two alternative hypotheses are stated in the following form:

H1.1. A firm's ESG disclosure has a negative relation with the firm's information asymmetry.

H1.2. A firm's ESG disclosure has a positive relation with the firm's information asymmetry.

We test this question to establish a formal link connecting ESG disclosure with voluntary earnings guidance through information asymmetry costs, which is our research question discussed in the next section.

2.2. ESG disclosure and earnings guidance

Although involvement in ESG disclosure represents an important way of providing information to the market, companies traditionally also use other ways to build a more transparent image and decrease information asymmetry. Earnings guidance reflects the voluntary disclosure of expected earnings by managers (Call et al., 2024; Chen et al., 2011; Palmon et al., 2023). Previous research provides evidence that earnings guidance has many benefits and is an important factor in reducing information asymmetry (Coller & Yohn, 1997; Diamond & Verrecchia, 1991; Verrecchia, 2001). For example, it may improve analyst forecast accuracy (Waymire, 1986), reduce the dispersion in analyst forecasts (Clement et al., 2003; Ruan et al., 2024), reduce litigation risk (Kasznik, 1999; Skinner, 1997), lower the bid-ask spread (Coller & Yohn, 1997), and decrease the probability of earnings management (Call et al., 2014; García Osma et al., 2023). It has also been observed that earnings guidance may help a company lower the cost of capital, enhance corporate investments and growth (Houston et al., 2010), and build a more transparent and credible image in the market (Hutton & Stocken, 2021).

Although earnings guidance reduces information asymmetry, it comes with costs. Kasznik (1999) finds that companies that issue guidance and overestimate earnings are characterized by significant levels of

discretionary accruals, leading to increased litigation risks. Verrecchia (1983) claims that earnings guidance leads to proprietary costs that are potentially damaging for a firm, especially when unfavorable information is released to the market (e.g., a bank would be tempted to ask for repayment of its loan). Managers' motivation to issue guidance may also result in jeopardizing future returns while boosting the firm's current capitalization level (Verrecchia, 2001). Issuing earnings guidance may distract the firm management by taking time from other valuable activities that could be devoted to running the business (Hutton & Weber, 2001). Feng and Koch (2010) provide evidence that earnings guidance generates costs for the firm in the form of legal liability, reputation loss, and stock price declines, especially when realized earnings fall short of management earnings predictions. Finally, Krishnan et al. (2012) observe that issuing guidance increases audit fees by about 7 % in the year of forecast disclosure. Therefore, researchers (e.g., Fields et al., 2001; Krishnan et al., 2012) suggest that companies carefully compare the benefits and costs while making decisions regarding issuing voluntary earnings guidance.

Although many determinants of voluntary earnings guidance have been examined in the previous literature, a firm's information asymmetry is considered the main cause. Coller and Yohn (1997) show that the management of firms with higher information asymmetry choose to provide guidance. Many researchers observe that low liquidity in the market intensifies the issuance of earnings guidance, as voluntary disclosure helps further improve transparency (Heflin et al., 2005; Welker, 1995). Wang (2007) finds that companies with low information asymmetry reduce or eliminate voluntary earnings guidance since the U. S. Regulation Fair Disclosure was enacted in 2001 as they face a "chilling effect." Numerous studies report that companies with higher institutional ownership are characterized by higher probability and quality of earnings guidance due to the high information demand from institutions (e.g., Ajinkya et al., 2005). At the same time, managerial guidance leads to a reduction in information asymmetry (Balakrishnan et al., 2014).

As some studies suggest that ESG disclosure represents an important way of building a transparent image, we expect that companies with better ESG disclosure are already characterized by lower information asymmetry. Therefore, managers of these companies are less likely to issue voluntary earnings guidance to save on disclosure costs. Thus, we believe that the level of a firm's involvement in ESG disclosure is a determining factor in managerial decisions to issue earnings guidance. We hypothesize that socially responsible companies have less need to provide guidance with higher precision, which might be associated with additional costs. We also expect that the relation with the probability of issuing earnings guidance is negative for the three pillars of ESG, as they follow the same objectives as overall involvement in ESG disclosure.

However, ESG disclosure is quite different from voluntary earnings guidance in information nature and its mechanism of information transparency improvement. Voluntary earnings guidance serves the main purpose of aligning market expectations with the upcoming release of mandatory earnings statements. While earnings guidance carries some costs, its major benefit is reduction in information asymmetry about the firm's future cash flows, and, thus, in the reduction of stock's price volatility and the cost of capital. ESG disclosure is unrelated to the timing of an information release but is linked to the presence of ESG activities as it serves a purpose of creating a more transparent and ESG-friendly image of a firm. While some studies find a positive association between ESG activities and firm risk reduction, which ultimately may reduce the cost of capital, ESG disclosure can be viewed as a broader tool for creating a transparent image for the firm.

At the same time, if ESG disclosure is associated with more information asymmetry due to the diversity and divergence of publicly provided ESG ratings and a firm's own ESG disclosures, then the relation between a firm's ESG disclosure and its earnings guidance practices may be positive. Coller and Yohn (1997) show that the management of firms with higher information asymmetry choose to provide earnings guidance. Thus, due to the subjectivity of ESG information (Kimbrough et al., 2022) and the lack of shared understanding of how to interpret it (Christensen et al., 2022), companies that disclose more ESG-related information may face an increase in information asymmetry. Therefore, managers of these companies will issue voluntary earnings guidance to reduce information asymmetry stemming from increased uncertainty about ESG disclosure. Moreover, management will issue more informative earnings guidance to build a more transparent image for stakeholders in the market. This discussion leads us to our main hypothesis expressed in the null form:

H2null. A firm's ESG disclosure, as well as each pillar, E, S, and G, have no association with the likelihood and informativeness of earnings guidance.

Our two alternative hypotheses are stated in the following form:

H2.1. A firm's ESG disclosure, as well as each pillar, E, S, and G, have a negative association with the likelihood and informativeness of earnings guidance.

H2.2. A firm's ESG disclosure, as well as each pillar, E, S, and G, have a positive association with the likelihood and informativeness of earnings guidance.

3. Data and variables

The data used to construct the sample and to calculate the variables of interest, as well as the control variables used in the study, come from the databases of the Institutional Brokers Estimate System (I/B/E/S) Guidance, Thomson Reuters Refinitiv Institutional (13f) Holdings - S34, Bloomberg, the Center for Research in Security Prices (CRSP), Compustat, and the I/B/E/S Academic. We also use 10-K filings obtained from the SEC website to construct our ESG disclosure proxy using a machine learning approach.

3.1. Voluntary managerial earning guidance

We collect voluntary managerial earnings guidance from Thomson Reuters I/B/E/S Guidance databases for the period 2002–2021.[3] Following Anilowski et al. (2007) and Agapova and Madura (2011), we retain the last management forecast of quarterly earnings and omit all other types and frequency of management forecasts. The procedure provides us with 11,481 firm-quarter observations and represents about 1 % of the sample before we merge it with firm ESG disclosure proxies. In our analysis of guiding firms, we divide the earnings forecasts into those that convey downward, upward, neutral, and undefined guidance (Agapova & Madura, 2011; Anilowski et al., 2007).[4]

3.2. Firm ESG disclosure proxies

Given a common observation among practitioners (Toplensky, 2022) and academics (Christensen et al., 2022; Kimbrough et al., 2022; Serafeim & Yoon, 2022) that ESG scores provided by different rating

[3] We begin our sample in 2002 to focus on the period after Regulation Fair Disclosure (Reg FD) was implemented in October 2001. Reg FD requires companies to disclose material information to all investors equally, ensuring fair access. This allows us to capture the current corporate disclosure environment. The sample period ends at the time of data collection.

[4] Using their own algorithm based on whether the announced guidance range or point estimate is above, below, or equal to analysts' mean forecast for the date, Thomson Reuters assigns four codes: 1—Earnings Shortfall (The company is not expected to meet earnings for the period indicated), 2—Beat Consensus (The company is expected to beat earnings for the period indicated), 3—Match Consensus (The company is expected to meet earnings for the period indicated), and 6—Management Guidance (The company has provided guidance but not specified whether they will meet, beat, or miss the street). The source is I/B/E/S Guidance User Guide July 2009.

agencies diverge significantly, we use two proxies for a firm's ESG disclosure.[5] Our first proxy for the firm's ESG disclosure is the Bloomberg ESG disclosure score, *Bloomberg ESG*. Bloomberg ESG disclosure score is widely used in previous studies (e.g., Buchanan et al., 2018; Christensen et al., 2022; Eliwa et al., 2021; Li et al., 2018). The score is assigned based on collected standardized data from annual reports, sustainability reports, corporate websites, and other sources, and ranges from 0.1 for companies with the minimum amount of ESG data to 100 for firms that disclose the complete set of indicators included in the Bloomberg ESG disclosure score. The Bloomberg disclosure score also allows for the evaluation of each of the ESG pillars: environmental, social, and governance. The environmental disclosure score includes (but is not limited to) the following dimensions: energy consumption, water use, methane emissions, and environmental fines. The social disclosure score is based on the number of employees, percentage of employees unionized, training policy, human rights policy, anti-bribery ethics policy, and UN Global Compact Signatory. The governance disclosure pillar includes the size of the board, the percentage of independent directors, the number of board meetings, and board meeting attendance.

Michelon et al. (2020) report that investors are even more concerned about ESG disclosure rather than the real implementation of ESG performance. That is driven by the observation that ESG disclosure has become "a compromise solution" for investors and the market, as ESG disclosure decreases the tension between the ideals of social justice and profit-seeking motivation (Michelon et al., 2020). We construct the *sec*ond proxy using a machine learning (ML) technique, namely, a word embedding model. It measures the quantity of ESG disclosure in firms' 10-K forms. Kimbrough et al. (2022) claim that management-provided ESG information can decrease the existing disagreement that arises due to use of management and non-management information in the construction of ESG indexes created by third parties. We draw insight from Li et al. (2021), who employ a word embedding model to measure corporate culture from analyst reports. Our word embedding model approach is beneficial for measuring abstract concepts, such as different dimensions of ESG (Li et al., 2021). Unlike more well-defined concepts (e.g., the tone of the business outlook), ESG can be described using less frequent words, phrases, and idioms that make sense only in a particular context. The machine learning approach can identify thousands of words and phrases related to each ESG dimension based on the context in which they appear. The word embedding approach uses a data-driven, objective approach to address the challenges of traditional text analysis in identifying correct phrases. The machine learning technique allows us to estimate the ESG disclosure from 10-K and 10-Q forms. As the training data, we use more than 460,000 10-K and 10-Q forms from the Edgar database (https://www.sec.gov/edgar/). Using ML, we create an extensive, high-quality dictionary from 10-K and 10-Q forms that correctly considers the context of the phrases (Bhatia et al., 2021). We use a neural network model (word2vec by Mikolov et al., 2013) to learn the vector representations for the dictionary words found in 10-K and 10-Q forms using the Gensim library (radimrehurek.com/gensim/) in Python. To build the measure, we use the 100 semantically most similar phrases in our dictionaries for the *environmental, social*, and *governance* dimensions of ESG. Next, we count the relative occurrences of these words and phrases in the 10-K forms to build a measure to estimate the amount of *environmental, social*, and *governance* discussion in companies' annual reports (as the amount of ESG phrases divided by the total number of phrases in the report). A detailed description of the method is provided in the Appendix. As the ESG scores obtained from databases do not directly reflect the amount of ESG-related information in companies' reports, the applied machine learning technique represents an efficient metric that specifically measures the amount of ESG disclosure.

[5] Toplensky (2022) states: "However, ESG is a slippery concept, without widely accepted definitions, criteria and metrics. Infamously, a single company's ESG rating can vary widely between credible credit-rating firms. That variance isn't unreasonable. There are many ways to combine the three criteria into one score, and for any single one there can be honest disagreement about what good or bad actually looks like. For example, some might rank Shell highly on 'E' because it has a plan to decarbonize its business, or poorly because it sells oil and plans to sell natural gas for years."

3.3. Information asymmetry proxies

We construct four information asymmetry proxies. The first one is the bid-ask spread (*Spread*), which is one of the most frequently used variables in the information asymmetry literature (e.g., Chen et al., 2007; Kelly & Ljungqvist, 2012; Llorente et al., 2002). It is the average of the daily relative quoted bid-ask spread for the quarter divided by the quote midpoint.

Our second measure of information asymmetry is the dispersion of analysts' forecasts (*AFDisp*), which captures differences in investor opinions through analysts' disagreement (Lang & Lundholm, 1996; Diether et al., 2002; Li & Zhao, 2008; Cui et al., 2018). We construct *AFDisp* as a quarterly average of the monthly dispersion of analysts' forecasts. The monthly analyst dispersion is measured as the standard deviation of analysts' current-quarter forecasts of earnings per share (EPS) available up to the given month, scaled by the absolute value of the mean forecast. The data on analysts' forecasts come from the Unadjusted Summary File of I/B/E/S Academic.

The third proxy for information asymmetry is volatility in market response to earnings announcements (Agapova & Volkov, 2019; Huang & Thakor, 2013; Kelly & Ljungqvist, 2012). This proxy of divergence in opinions among market participants allows us to capture information asymmetry among informed and uninformed investors. Earnings announcement standard deviation (*EarnAnnVol*) is the standard deviation of the three-day $(-1, +1)$ cumulative abnormal returns around a firm's quarterly earnings announcements for the past five years. Similar to Huang and Thakor (2013), we use the equally weighted CRSP index and an estimation window of $(-205, -6)$ to calculate the CARs using a market model. At least four observations must be present to calculate the standard deviation. This variable measures the element of consistency in investors' expectations regarding a firm's earnings. A higher standard deviation of CARs implies a higher level of inconsistency in expectations and, thus, a higher level of information asymmetry.

Our fourth measure of information asymmetry is the logarithm of the Amihud illiquidity measure (*LogAIM*), a stock illiquidity measure. The measure is calculated based on Amihud (2002) as $AIM_i = \frac{1}{D}\sum_{d=1}^{D}\frac{|R_{i,d}|}{VOLD_{i,d}}$, where $R_{i,d}$ is the return of stock i on day d measured as a decimal; $VOLD_{i,d}$ is the dollar volume of stock i traded on day d, calculated as the closing price of the stock times the number of shares traded on the given date, measured in millions of dollars; and D is the number of the days in a quarter. As the distribution of *AIM* is highly skewed, a log-transformed version of *AIM* is generated, as in Dick-Nielsen et al. (2012).

3.4. Control variables

The following control variables are likely to affect a firm's decision to voluntarily provide earnings guidance (Agapova & Madura, 2016; Welker, 1995):

Institutional Investors Holdings (*InstHold*): The proportion of a firm owned by institutional investors is calculated as the ratio of the number of shares owned by such investors to the total number of shares outstanding in the quarter. Higher institutional ownership should be associated with a higher demand for information. The data come from Thomson Reuters Institutional (13f) Holdings - S34.

Analysts: The variable is calculated as the log of 1 plus the number of analysts who follow the firm in the quarter. This variable is also a proxy for information demand. A higher number of analysts should result in a higher probability of disclosure. The data come from I/B/E/S Academic.

Analyst Forecast Error (*AFE*): Consensus analysts' forecast error is

calculated as I/B/E/S actual earnings minus the most recent median consensus forecast scaled by price, in percentage. The data source is I/B/E/S Academic.

Size: A firm's size is calculated as the log of the market capitalization of the firm. Larger firms may have a greater following in terms of investors and analysts, and therefore will naturally have a higher demand for information. The data come from CRSP.

B/M: This variable is book-to-market, a standard control for firm characteristics, such as the ability of a firm to generate high returns on its investments. In other studies, the B/M ratio is used as a proxy for various other firm characteristics (e.g., growth opportunities and degree of managerial discipline). The data come from Compustat and CRSP.

AgeFirm: This variable is the age of the firm in years (since its appearance in the CRSP database).

Table 1
Descriptive statistics.
Panel A of the table reports descriptive statistics of the main and explanatory variables. Panel B presents statistics of the firms' coverage by Bloomberg ESG disclosure score for the whole sample and by year. The variables are described in Section 3. *, **, and *** indicate significance at the 10 %, 5 %, and 1 % levels, respectively.

Panel A	All			Guide			Do not guide				
Variable	Obs	Mean	Std. Dev.	Obs	Mean	Std. Dev	Obs	Mean	Std. Dev	Mean Diff	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(5)–(8)	
guide	54,878	0.039	0.194								
Bloom ESG	27,515	35.6	10.1	767	36.4	9.2	26,748	35.6	10.1	0.8	**
Bloom E	27,584	10.3	17.2	768	11.5	16.8	26,816	10.3	17.2	1.3	**
Bloom S	27,585	12.6	11.8	768	12.8	10.0	26,817	12.6	11.8	0.2	
Bloom G	27,588	83.7	4.9	768	84.8	4.0	26,820	83.7	5.0	1.0	***
ML ESG	53,977	0.081	0.041	2043	0.089	0.040	51,934	0.081	0.041	0.009	***
ML E	53,977	0.116	0.073	2043	0.131	0.071	51,934	0.116	0.073	0.015	***
ML S	53,977	0.017	0.029	2043	0.022	0.029	51,934	0.016	0.029	0.006	***
ML G	53,977	0.110	0.061	2043	0.114	0.060	51,934	0.110	0.061	0.005	***
Information Asymmetry											
spread	54,878	0.149	0.263	2161	0.167	0.265	52,717	0.148	0.263	0.019	***
logAIM	54,878	0.008	0.071	2161	0.012	0.112	52,717	0.008	0.069	0.004	***
AFdisp	54,878	19.65	84.660	2161	10.394	26.041	52,717	20.029	86.196	−9.635	***
EarnAnnVol	54,878	7.244	3.579	2161	9.592	3.702	52,717	7.148	3.541	2.445	***
Controls (whole sample)											
InstHold	54,878	77.82	20.757	2161	83.83	17.357	52,717	77.57	20.848	6.262	***
Analysts	54,878	2.258	0.603	2161	2.285	0.587	52,717	2.257	0.604	0.028	**
AFE	54,878	−0.193	15.537	2161	−0.130	6.647	52,717	−0.195	15.795	0.066	
Size	54,878	7.771	1.580	2161	7.248	1.405	52,717	7.792	1.583	−0.544	***
BM	54,878	0.604	0.636	2161	0.485	0.334	52,717	0.609	0.645	−0.124	***
AgeFirm	54,878	24.72	19.624	2161	11.72	7.448	52,717	25.26	19.784	−13.537	***
Turnover	54,878	10.14	8.539	2161	10.54	6.929	52,717	10.12	8.598	0.419	**
Beta	54,878	1.139	0.434	2161	1.201	0.428	52,717	1.137	0.434	0.064	***
IVOL	54,878	0.021	0.012	2161	0.023	0.010	52,717	0.020	0.012	0.003	***
BMdisp	54,878	2.177	31.135	2161	0.701	3.285	52,717	2.238	31.759	−1.537	**
Litigation	54,878	0.035	0.185	2161	0.105	0.307	52,717	0.033	0.178	0.072	***
ManHold	54,878	2.691	6.220	2161	2.901	6.347	52,717	2.682	6.215	0.219	*
Controls (guiding firms)											
Precision				2161	2.103	0.358					
G_Duration				2161	81.560	35.995					

Panel B: Bloomberg coverage	Period	Obs	Mean	Std. Dev.
D_Bloom	whole sample	54,878	0.501	0.500
Treat	whole sample	54,878	0.656	0.475
Always Coverage	whole sample	54,878	0.122	0.328
D_Bloom	2002	1848	0	0
D_Bloom	2003	3817	0	0
D_Bloom	2004	3867	0.002	0.039
D_Bloom	2005	2790	0.054	0.227
D_Bloom	2006	1996	0.098	0.298
D_Bloom	2007	1142	0.343	0.475
D_Bloom	2008	4477	0.417	0.493
D_Bloom	2009	4451	0.454	0.498
D_Bloom	2010	4459	0.621	0.485
D_Bloom	2011	3351	0.659	0.474
D_Bloom	2012	1146	0.693	0.462
D_Bloom	2013	2330	0.713	0.453
D_Bloom	2014	4681	0.724	0.447
D_Bloom	2015	4648	0.762	0.426
D_Bloom	2016	3387	0.810	0.392
D_Bloom	2017	2215	0.847	0.360
D_Bloom	2018	1095	0.879	0.327
D_Bloom	2019	2138	0.915	0.278
D_Bloom	2020	1040	0.940	0.237

Turnover: This variable is the average daily trading volume of the stock's shares in the quarter, divided by the average of the total number of shares outstanding in that quarter. This variable proxies for the liquidity of the firm's stock. The data source is CRSP.

Beta: This proxy represents the systematic risk of the firm, calculated using the Beta Suite by WRDS for the period of one year preceding the quarter of interest. Firms with more systematic risk have a higher cost of equity. Such firms are more likely to issue earnings guidance to reduce the cost of equity through the reduction of information asymmetry. The data source is CRSP.

Residual Standard Deviation (IVol): This proxy represents the firm's idiosyncratic risk, calculated as the standard deviation of the error term from the market model, calculated for the period of one year preceding the quarter of interest. The data source is CRSP.

Market to Book (MTB) Dispersion: A higher dispersion of market-to-book ratios in an industry implies a higher level of uncertainty and information asymmetry about that industry. This proxy is calculated as the standard deviation of the market-to-book ratios of firms in the same industry, based on the first two digits of the SIC in a given quarter. The data sources are Compustat and CRSP.

Litigation: Reduction in litigation costs is one of the identified drivers of voluntary managerial earnings guidance (Field et al., 2005; Skinner, 1997). Thus, we control for industries that are more prone to litigation. The litigation variable is set equal to 1 if the firm is a member of one of the high-litigation-risk industries: biotechnology (SIC codes 2833–2836, SIC codes 8731–8734), computer (SIC codes 3570–3577, SIC codes 7370–7374), electronics (SIC codes 3600–3674), and retail (SIC codes 5200–5961).

Management Holdings (ManHold): Firm stock holdings by management are calculated as the sum of shares owned by management over the total shares outstanding in percentage. Managerial ownership is another proxy for information asymmetry surrounding a firm. Higher managerial ownership indicates lower information asymmetry and, as a result, is associated with lower likelihood of earnings guidance. The data source is Compustat Execucomp.

Precision: The precision of company-issued guidance equals three if a point estimate, two if a range estimate, and one if an open interval (Agapova et al., 2022).

Guidance Duration (*G_Duration*): Days between guidance issue and earnings announcement (Agapova et al., 2022).

4. Empirical analysis

4.1. Descriptive statistics

Table 1, Panel A reports descriptive statistics of the main explanatory and control variables for the whole sample and for firms that issue voluntary earnings guidance and those that do not. Only 4 % of the sample firms issue earnings guidance. Based on the univariate analysis, we observe noticeable differences in the characteristics of the firms that provide guidance regarding upcoming earnings releases and those that do not. The Bloomberg and ML scores are higher for guiding firms than non-guiding ones. Consistent with information and cost reduction hypotheses, we also observe firm characteristics for guiding firms that indicate more information asymmetry (larger earnings announcement standard deviation (*EarnAnnVol*), bid-ask spread (*Spread*) and the log Amihud Illiquidity Measure (*logAIM*), and younger firms), higher information demand (more institutional holdings and analyst coverage), and more risk (higher beta and idiosyncratic risk, and belonging to industries that are prone to litigation).

Panel B of the table reports statistics on Bloomberg ESG disclosure coverage of the sample firms. Within the full sample, 50.1 % of the firm-quarter observations have had coverage by Bloomberg ESG disclosure scores, 65.6 % of the firm-quarter observations are the ones that had the coverage initiated during or before the sample period with 12.2 % of those observations being always covered and not experiencing initiation of coverage during the study period. A control group that did not have the Bloomberg coverage initiated is 34.3 % of the firm-quarter observations. We observe a steady increase in the percentage of firms covered by Bloomberg ESG disclosure scores from 0.02 % in 2004 to 94 % in 2020.

Table 2 reports the correlation coefficients between the variables. Panel A of the table illustrates that Bloomberg E, S and G pillars have 0.96, 0.93, and 0.66 correlation coefficients with Bloomberg total ESG score, correspondingly. Panel A also illustrates the high correlation of machine learning E, S, and G pillars with ML total ESG score with 0.86, 0.55, and 0.74 correlation coefficients, correspondingly, but noticeably lower than those of Bloomberg scores. What is surprising is that Bloomberg ESG score and ML ESG score have a very low correlation at 0.03. Bloomberg and ML individual pillars, E, S, and G, also have low correlation at 0.04, 0.04, and 0.03, correspondingly. ML E, S, and G pillars have lower correlation among themselves, ranging 0.26–0.40, in comparison to Bloomberg E, S, and G pillars correlations of 0.53–0.82, with the highest correlation between E and S pillars (0.82 for Bloomberg E and S, and 0.40 for ML E and S). The results in Panel B of Table 2 show that the right-hand-side variables in our regression models do not have high enough correlations to pose a multicollinearity problem for the multivariate analyses.

4.2. ESG disclosure and information asymmetry

As we argue in Section 2, the information hypothesis is a primary link between the expected relation between ESG disclosure and the likelihood of issuing earnings guidance. Before testing our hypotheses of the effects of ESG practices on voluntary earnings guidance, we analyze a link between ESG disclosure and information asymmetry surrounding a firm. Although Cui et al. (2018) find that CSR scores negatively relate to the information asymmetry of a company, their tests are limited to only some aspects of ESG performance and for earlier and shorter periods of time when ESG following was scarcer than the period in our tests.

Our goal is to study the effects of ESG disclosure on the information asymmetry of a firm. The formal model is described in Eq. (1) below and is estimated using ordinary least square (OLS) fixed-effects panel estimation techniques. The analysis is applied to panel data at the firm level.

$$IA_{it} = \beta_0 + \beta_1 ESG_{it} + \theta X_{it} + \delta_t + \gamma_i + \varepsilon_{it}, \quad (1)$$

where the dependent variable IA_{it}, a measure of information asymmetry of firm i in quarter t, is one of the following: bid-ask *Spread*, logarithm of the Amihud illiquidity measure (*LogAIM*), and analysts' forecast dispersion (*AFDisp*) *volatility* in market response to earnings announcements (*EarnAnnVol*). The main explanatory variable is $(ESG)_{it}$, which is one of our two measures of ESG disclosure: the *Bloomberg ESG* disclosure score and three of its pillars, the environmental *Bloomberg E*, social *Bloomberg S*, and governance *Bloomberg G* disclosure scores; and the machine learning (ML) approach ESG disclosure score constructed based on 10-K reports and its three pillars ML E, ML S, and ML G.

The parameter β gives the change in information asymmetry per unit of ESG score change. This parameter is expected to be negative if ESG disclosure decreases information asymmetry (H1.1) or positive if ESG disclosure increases information asymmetry (H1.2). Other explanatory variables included in vector $\boldsymbol{X}$ that contain firm- and quarter-specific characteristics are *InstHold*, *Analysts*, *Size*, *BM*, *AgeFirm*, and *Turnover*. Year fixed effects, represented by δ_t, control for year trends, and industry-specific unobserved characteristics are accommodated through an industry fixed effect γ_i. ε_{it} is the error term, with standard errors clustered at the firm level.

Table 3 reports the results of the model in Eq. (1) tests of the ESG disclosure scores on information asymmetry proxies. The results for the models with total Bloomberg scores (columns (1)–(4)) and machine learnings scores (columns (5)–(8)) as proxies for ESG disclosure, reported in panel A, show that the overall ESG scores have a positive

Table 2
Correlations.
The table reports Pearson correlation coefficients between variables for a maximum of 54,878 firm-quarter observations from 2002 to 2021. Panel A reports statistics on ESG disclosure scores. Panel B reports the statistics on the explanatory variables.

Panel A	Bloom ESG	Bloom E	Bloom S	Bloom G	ML ESG	ML E	ML S	ML G
Bloom ESG	1.00							
Bloom E	0.96	1.00						
Bloom S	0.93	0.82	1.00					
Bloom G	0.66	0.53	0.56	1.00				
ML ESG	0.03	0.05	0.04	−0.02	1.00			
ML E	0.01	0.04	0.05	−0.04	0.86	1.00		
ML S	0.04	0.06	0.04	−0.01	0.55	0.40	1.00	
ML G	0.04	0.04	0.00	0.03	0.74	0.33	0.26	1.00

Panel B		(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
InstHold	(1)	1.00										
Analysts	(2)	0.16	1.00									
AFE	(3)	0.01	0.01	1.00								
Size	(4)	0.00	0.66	0.02	1.00							
BM	(5)	−0.05	−0.13	−0.09	−0.21	1.00						
AgeFirm	(6)	−0.14	0.09	0.00	0.40	0.02	1.00					
Turnover	(7)	0.26	0.21	−0.06	−0.05	0.09	−0.14	1.00				
Beta	(8)	0.09	0.01	−0.03	−0.18	0.13	−0.15	0.32	1.00			
IVOL	(9)	−0.03	−0.20	−0.07	−0.48	0.27	−0.28	0.41	0.38	1.00		
BMDisp	(10)	0.00	0.01	0.00	0.00	0.02	0.00	0.00	0.01	0.00	1.00	
Litigation	(11)	0.03	0.02	0.00	−0.03	−0.07	−0.11	0.03	0.02	0.05	−0.01	1.00
ManHold	(12)	−0.13	−0.12	0.00	−0.17	−0.02	−0.15	−0.01	0.00	0.09	0.00	0.05

relation for all measures of information asymmetry, indicating an increase in information asymmetry with more ESG disclosure. However, the Bloomberg ESG coefficient is statistically significant at 1 %–5 % level in models with *Spread*, *logAIM* and *AFDisp* but not significant in *EarnAnnVol* model. Also, the ML ESG coefficient is statistically significant at 1 %–10 % in models with *Spread*, *AFDisp*, and *EarnAnnVol* but not significant in *logAIM* model. This result is consistent with the argument that more ESG disclosures may lead to more confusion among market participants. Panel B and C of Table 3 reports results for models with Bloomberg E, S and G pillars and ML E, S, and G pillars as main explanatory variables, accordingly. Bloomberg E pillar coefficient has similar statistical significance results of Eq. (1) model to the total Bloomberg ESG score coefficient but has higher economic significance. Bloomberg S pillar coefficients are highly economically and statistically significant in models with *Spread* and *logAIM* information asymmetry proxies but statistically insignificant in *AFDisp*, and *EarnAnnVol* models. Bloomberg G pillar has positive relation with three information asymmetry proxies but is statistically insignificant. Finally, the coefficients of ML E, S and G pillars scores are all positive in all models with dependent variable information asymmetry proxied with *Spread*, *AFDisp*, *EarnAnnVol* and *logAIM*. However, only ML S scores coefficients are statistically significant at 1 %–5 % level with all proxies of information asymmetry. Overall, the results point to a positive relation between firm ESG disclosure and information asymmetry.

4.3. ESG disclosure and the likelihood of earnings guidance

To test our second, and main, hypothesis of whether ESG disclosure affects the likelihood of issuing managerial earnings guidance and its precision, we apply multivariate logit (and linear probability model) and ordered logit models, accordingly, to determine whether the probability of issuing guidance (accounting for the precision of guidance) is associated with levels of ESG disclosure.[6] The model is the following, which is estimated controlling for the industry and fiscal quarter fixed effects with standard errors clustered at the firm level:

$$Guide_{it} = \alpha_0 + \alpha_1 ESG_{it-1} + \theta X_{it-1} + \delta_t + \gamma_i + \varepsilon_{it}, \quad (2)$$

where the dependent variable *Guide* is 1 if firm *i* issues guidance in quarter *t* and 0 otherwise, in the logit model, and equals 1 if the firm issues open interval earnings guidance for quarter *t*, 2 if the firm issues range guidance for quarter *t*, 3 if the firm issues point guidance for quarter *t*, and 0 otherwise, ordered logit model. The main explanatory variable, *ESG*, is one of the following lagged firm ESG disclosure proxies: the *Bloomberg ESG* disclosure score and its three pillars (*Bloomberg E*, *Bloomberg S*, and *Bloomberg G*), and the ML ESG disclosure score and its three pillars (*ML E*, *ML S*, and *ML G*).

The parameter β gives the propensity score of earnings guidance per unit of ESG score change. As H2 is an empirical question, β can be either negative or positive depending on what drives the connection between ESG practices and earnings guidance strategy. Other explanatory variables included in vector ***X*** that contain lagged firm- and quarter-specific characteristics are *InstHold*, *Analysts*, *AFE*, *Size*, *BM*, *AgeFirm*, *Turnover*, *Beta*, *IVol*, *MTB*, *Litigation*, and *ManHold*. Fiscal quarter fixed effects, represented by δ_t, control for quarterly macro-trends, and industry-specific unobserved characteristics are accommodated through an industry fixed effect, γ_i. ε_{it} is the error term.

Table 4 reports the results of the full model specified in Eq. (2) for logit regression (columns (1)–(4)), and linear probability model (columns (5)–(8)): *Bloomberg ESG* in Panel A and *ML ESG* in Panel B.[7] Our findings reflect that ESG disclosure and disclosure of information about all three ESG pillars are positively related to issuing earnings guidance (logit) and issuing more precise guidance (ordered logit). The results show that ESG disclosure scores and all three of their pillars have positive and significant coefficients. Given our results on the positive relation between ESG disclosure and information asymmetry, the positive relation between ESG disclosure and earnings guidance can be explained by firms' use of earnings guidance as a mitigating mechanism to the adverse effects of ESG disclosure on firm transparency.

Confirming our expectations and previous literature findings, we

[6] Our method is similar to the prior studies examining the likelihood of earnings guidance in the sample of relatively infrequent occurrence of earnings guidance (e.g., Agapova et al., 2022; Francoeur et al., 2023)

[7] Ordered logit regression results are similar and untabulated.

Table 3

Effect of ESG disclosure on firm information asymmetry.

The table reports the results of fixed-effects OLS regressions of the proxies for ESG disclosure on information asymmetry proxies. The dependent variable is one of three proxies of information asymmetry: bid-ask spread (spread), log of Amihud illiquidity measure (*logAIM*), the dispersion of analysts' forecasts (*AFDisp*), and earnings announcements CAR standard deviation (*EarnAnnVol*). Control variables (not reported in the tables for brevity) are *InstHold*, *Analysts*, *Analyst Forecast Error*, *Size*, *B/M*, *AgeFirm*, and *Turnover*. Panels A reports the results for the models with the Bloomberg and machine learning total ESG scores, and panels B and C those with the Bloomberg and machine learning, S and G scores, respectively. The OLS models control for year and industry fixed effects; standard errors are clustered by firm, and t-stats are reported below the coefficients. *, ** and *** indicate statistical significance at less than the 10 %, 5 %, and 1 % levels, respectively.

Panel A	Spread	logAIM	AFDisp	EarnAnnVol	Spread	logAIM	AFDisp	EarnAnnVol
	Bloomberg				Machine Learning			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
ESG score	0.002***	0.001***	0.255**	0.002	0.072**	0.011	17.339*	2.435***
	(4.095)	(3.146)	(2.137)	(0.227)	(2.382)	(1.433)	(1.783)	(3.658)
InstHold	−0.002***	−0.000***	−0.054	0.001	−0.002***	−0.000***	−0.037	−0.001
	(−5.400)	(−2.941)	(−1.420)	(0.522)	(−6.868)	(−4.979)	(−1.363)	(−0.444)
Analysts	0.014*	0.006**	0.464	0.341***	0.018***	0.007***	−0.774	0.316***
	(1.904)	(2.238)	(0.261)	(2.730)	(3.197)	(3.901)	(−0.617)	(3.292)
Size	−0.049***	−0.009***	−5.899***	−0.698***	−0.059***	−0.010***	−4.932***	−0.788***
	(−7.502)	(−3.716)	(−6.641)	(−11.687)	(−15.464)	(−7.949)	(−8.491)	(−17.351)
B/M	0.026***	0.003*	10.468***	−0.188*	0.050***	0.008***	9.123***	−0.067
	(3.853)	(1.668)	(4.978)	(−1.659)	(5.226)	(4.508)	(3.981)	(−1.114)
AgeFirm	−0.000***	−0.000**	−0.078	−0.027***	0.000	−0.000	0.006	−0.029***
	(−2.722)	(−1.993)	(−1.549)	(−9.308)	(0.565)	(−0.545)	(0.143)	(−11.778)
Turnover	−0.001***	−0.000***	0.881***	0.074***	−0.003***	−0.001***	0.604***	0.069***
	(−3.064)	(−3.561)	(6.033)	(8.592)	(−8.292)	(−6.697)	(6.835)	(11.750)
Intercept	0.562***	0.084***	24.558**	15.147***	1.122***	0.096***	74.434***	13.919***
	(9.306)	(3.591)	(2.446)	(12.926)	(19.738)	(7.498)	(4.228)	(30.250)
Industry FE	X	X	X	X	X	X	X	X
Year FE	X	X	X	X	X	X	X	X
N	27,515	27,515	27,515	27,515	53,977	53,977	53,977	53,977
R^2	0.229	0.058	0.043	0.407	0.372	0.075	0.034	0.382

Panel B	Spread	logAIM	AFDisp	EarnAnnVol	Spread	logAIM	AFDisp	EarnAnnVol	Spread	logAIM	AFDisp	EarnAnnVol
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Bloom E	0.0009***	0.0002***	0.1436**	0.0016								
	(4.567)	(3.429)	(2.249)	(0.442)								
Bloom S					0.0016***	0.0004***	0.1497	−0.0013				
					(4.529)	(3.562)	(1.385)	(−0.245)				
Bloom G									0.0003	0.0003	0.1140	−0.0012
									(0.364)	(1.055)	(0.722)	(−0.128)
InstHold	−0.002***	−0.0004***	−0.0517	0.0013	−0.002***	−0.001***	−0.0568	0.0012	−0.002***	−0.001***	−0.0593	0.0012
	(−5.352)	(−2.903)	(−1.356)	(0.481)	(−5.367)	(−2.915)	(−1.524)	(0.444)	(−5.342)	(−2.940)	(−1.597)	(0.464)
Analysts	0.0143*	0.0066**	0.5053	0.3446***	0.0132*	0.0063**	0.5169	0.3503***	0.0160**	0.0070**	0.7754	0.3482***
	(1.953)	(2.252)	(0.285)	(2.761)	(1.849)	(2.201)	(0.292)	(2.791)	(2.105)	(2.319)	(0.439)	(2.802)
Size	−0.048***	−0.009***	−5.843***	−0.703***	−0.048***	−0.009***	−5.608***	−0.690***	−0.043***	−0.008***	−5.176***	−0.694***
	(−7.731)	(−3.753)	(−6.456)	(−11.891)	(−7.654)	(−3.785)	(−6.772)	(−11.619)	(−7.557)	(−3.576)	(−6.160)	(−12.232)
B/M	0.0265***	0.0036*	10.4932***	−0.1929*	0.0266***	0.0037*	10.7151***	−0.1848	0.0297***	0.0044**	10.9129***	−0.1873*
	(3.910)	(1.717)	(5.075)	(−1.696)	(3.959)	(1.762)	(4.957)	(−1.635)	(4.434)	(2.055)	(5.122)	(−1.667)
AgeFirm	−0.0003***	−0.0001*	−0.0750	−0.0274***	−0.0003***	−0.0001**	−0.0717	−0.0273***	−0.0002**	−0.0001	−0.0663	−0.0273***
	(−2.632)	(−1.948)	(−1.480)	(−9.379)	(−2.724)	(−2.009)	(−1.493)	(−9.296)	(−2.073)	(−1.559)	(−1.327)	(−9.284)
Turnover	−0.001***	−0.001***	0.8811***	0.0741***	−0.001***	−0.001***	0.8763***	0.0739***	−0.001***	−0.001***	0.8765***	0.0739***
	(−3.044)	(−3.524)	(6.047)	(8.598)	(−3.088)	(−3.541)	(6.016)	(8.593)	(−3.147)	(−3.601)	(6.018)	(8.591)
Intercept	0.5997***	0.0940***	30.6671***	15.2144***	0.6064***	0.0954***	29.4947***	15.1403***	0.5542***	0.0687***	17.9606	15.2473***
	(8.950)	(3.609)	(3.022)	(12.874)	(8.883)	(3.611)	(3.125)	(12.905)	(9.759)	(4.183)	(1.158)	(11.556)
Yr FE	X	X	X	X	X	X	X	X	X	X	X	X

(*continued on next page*)

Table 3 (*continued*)

Panel B	Spread	logAIM	AFDisp	EarnAnnVol	Spread	logAIM	AFDisp	EarnAnnVol	Spread	logAIM	AFDisp	EarnAnnVol
Ind FE	X	X	X	X	X	X	X	X	X	X	X	X
N	27,584	27,584	27,584	27,584	27,585	27,585	27,585	27,585	27,588	27,588	27,588	27,588
R^2	0.228	0.057	0.043	0.407	0.228	0.057	0.043	0.407	0.224	0.055	0.043	0.407

Panel C	Spread	logAIM	AFDisp	EarnAnnVol	Spread	logAIM	AFDisp	EarnAnnVol	Spread	logAIM	AFDisp	EarnAnnVol
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
ML E	0.024	0.002	7.073	1.020**								
	(1.276)	(0.406)	(1.439)	(2.405)								
ML S					0.241***	0.024**	33.464**	3.538***				
					(3.890)	(2.052)	(2.086)	(3.621)				
ML G									0.008	0.006	5.606	1.010
									(0.404)	(1.235)	(0.876)	(2.263)
InstHold	−0.002***	−0.000***	−0.037	−0.001	−0.002***	−0.000***	−0.036	−0.001	−0.002***	−0.000***	−0.037	−0.001
	(−6.875)	(−4.983)	(−1.385)	(−0.481)	(−6.869)	(−4.978)	(−1.354)	(−0.443)	(−6.876)	(−4.983)	(−1.368)	(−0.444)
Analysts	0.018***	0.007***	−0.791	0.314***	0.018***	0.007***	−0.801	0.314***	0.018***	0.007***	−0.746	0.321***
	(3.183)	(3.890)	(−0.630)	(3.262)	(3.158)	(3.886)	(−0.638)	(3.265)	(3.204)	(3.912)	(−0.593)	(3.335)
Size	−0.059***	−0.010***	−4.931***	−0.788***	−0.059***	−0.010***	−4.929***	−0.787***	−0.059***	−0.010***	−4.908***	−0.785***
	(−15.476)	(−7.957)	(−8.506)	(−17.317)	(−15.467)	(−7.952)	(−8.492)	(−17.309)	(−15.422)	(−7.934)	(−8.469)	(−17.289)
B/M	0.050***	0.008***	9.115***	−0.068	0.050***	0.008***	9.143***	−0.065	0.050***	0.008***	9.118***	−0.067
	(5.223)	(4.504)	(3.977)	(−1.134)	(5.235)	(4.517)	(3.988)	(−1.084)	(5.228)	(4.506)	(3.983)	(−1.119)
AgeFirm	0.000	−0.000	0.005	−0.029***	0.000	−0.000	0.006	−0.029***	0.000	−0.000	0.006	−0.029***
	(0.545)	(−0.554)	(0.127)	(−11.788)	(0.619)	(−0.523)	(0.162)	(−11.744)	(0.564)	(−0.534)	(0.148)	(−11.741)
Turnover	−0.003***	−0.001***	0.604***	0.069***	−0.003***	−0.001***	0.600***	0.068***	−0.003***	−0.001***	0.603***	0.069***
	(−8.286)	(−6.692)	(6.837)	(11.742)	(−8.346)	(−6.724)	(6.758)	(11.696)	(−8.299)	(−6.704)	(6.829)	(11.766)
Intercept	1.124***	0.096***	75.020***	13.999***	1.124***	0.096***	75.253***	14.043***	1.125***	0.096***	74.899***	13.959***
	(19.786)	(7.516)	(4.241)	(31.308)	(19.923)	(7.562)	(4.248)	(31.366)	(19.821)	(7.536)	(4.289)	(29.016)
Yr FE	X	X	X	X	X	X	X	X	X	X	X	X
Ind FE	X	X	X	X	X	X	X	X	X	X	X	X
N	53,977	53,977	53,977	53,977	53,977	53,977	53,977	53,977	53,977	53,977	53,977	53,977
R^2	0.372	0.075	0.034	0.382	0.373	0.075	0.034	0.382	0.372	0.075	0.034	0.382

Table 4

Effect of ESG disclosure on the likelihood of voluntary earnings guidance.

This table presents the results of the analysis of the likelihood of management earnings guidance issue from logit regressions, where the dependent variable (*Guide*) equals 1 if the firm issues earnings guidance for quarter *t* and 0 otherwise. The main explanatory variable is a lag of 1 of the proxies for firm ESG disclosure: the ESG total score and its three pillars Environmental (E), Social (S), and Governance (G). Panel A: the Bloomberg scores (logit model – columns (1)–(4)), Linear Probability Model – columns (5)–(8)). Panel B: the machine learning scores (logit model – columns (1)–(4)), Linear Probability Model – columns (5)–(8)). All other control variables are defined in Section 3. All regressions control for fiscal quarter and industry fixed effects. Robust standard errors are clustered by firm, and t-stats are reported below the coefficients. *, **, and *** indicate significance at the 10 %, 5 %, and 1 % levels, respectively.

Panel A	Logit				Linear Probability Model			
	Guide				Guide			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Bloom ESG $_{t-1}$	0.059***				0.0013***			
	(5.582)				(4.295)			
Bloom E $_{t-1}$		0.026***				0.0006***		
		(4.043)				(3.200)		
Bloom S $_{t-1}$			0.039***				0.0008***	
			(4.936)				(3.664)	
Bloom G $_{t-1}$				0.140***				0.0024***
				(6.512)				(5.091)
InstHold	0.012**	0.011**	0.011**	0.009**	0.0002*	0.0002*	0.0002*	0.0002
	(2.565)	(2.427)	(2.350)	(2.056)	(1.800)	(1.764)	(1.667)	(1.505)
Analysts	0.661**	0.638**	0.673**	0.748***	0.0154**	0.0152**	0.0154**	0.0172**
	(2.281)	(2.222)	(2.316)	(2.577)	(2.008)	(1.985)	(2.016)	(2.241)
AFE	−0.011***	−0.010***	−0.010***	−0.015***	−0.0002***	−0.0002**	−0.0002**	−0.0002***
	(−3.235)	(−3.022)	(−3.103)	(−4.387)	(−2.678)	(−2.485)	(−2.539)	(−3.081)
Size	−0.278**	−0.217*	−0.235*	−0.213*	−0.0064*	−0.0052	−0.0051	−0.0041
	(−2.235)	(−1.788)	(−1.894)	(−1.792)	(−1.936)	(−1.580)	(−1.581)	(−1.339)
BM	−0.318	−0.248	−0.244	−0.256	−0.0035	−0.0029	−0.0024	−0.0024
	(−1.148)	(−0.922)	(−0.910)	(−0.972)	(−1.175)	(−0.960)	(−0.801)	(−0.833)
AgeFirm	−0.049***	−0.047***	−0.048***	−0.051***	−0.0008***	−0.0007***	−0.0007***	−0.0007***
	(−6.270)	(−6.118)	(−6.162)	(−6.289)	(−5.061)	(−4.981)	(−4.986)	(−4.952)
Turnover	−0.041**	−0.042***	−0.042***	−0.040**	−0.0007***	−0.0007***	−0.0007***	−0.0007***
	(−2.562)	(−2.678)	(−2.636)	(−2.553)	(−2.641)	(−2.666)	(−2.729)	(−2.754)
Beta	0.052	0.043	0.083	0.082	0.0015	0.0009	0.0015	−0.0001
	(0.195)	(0.161)	(0.307)	(0.306)	(0.242)	(0.145)	(0.239)	(−0.021)
Ivol	−1.898	−1.278	−3.380	−2.125	−0.0835	−0.0677	−0.0912	0.0134
	(−0.199)	(−0.139)	(−0.355)	(−0.208)	(−0.445)	(−0.361)	(−0.487)	(0.072)
BMdisp	−0.001	−0.001	−0.001	−0.001	−0.0000	−0.0000	−0.0000	−0.0000
	(−0.576)	(−0.638)	(−0.533)	(−0.436)	(−0.356)	(−0.321)	(−0.215)	(−0.040)
Litigation	−0.011	0.029	0.010	0.053	0.0289	0.0297	0.0299	0.0315
	(−0.026)	(0.067)	(0.022)	(0.119)	(0.735)	(0.756)	(0.758)	(0.803)
ManHold	−0.038	−0.041	−0.041	−0.039	−0.0009*	−0.0010*	−0.0009*	−0.0009*
	(−1.312)	(−1.414)	(−1.353)	(−1.230)	(−1.823)	(−1.924)	(−1.867)	(−1.749)
Intercept	−2.94***	−1.578	−1.715	−13.337***	−0.0366	−0.0082	−0.0078	−0.2196***
	(−2.775)	(−1.419)	(−1.545)	(−7.676)	(−1.580)	(−0.329)	(−0.316)	(−5.372)
Fisc qtr FE	X	X	X	X	X	X	X	X
Ind FE	X	X	X	X	X	X	X	X
N	23,210	23,275	23,275	23,275	27,109	27,183	27,183	27,186
Pseudo R^2 / R^2	0.2153	0.2087	0.2083	0.2219	0.0711	0.0699	0.0695	0.0718

Panel B	Logit				Linear Probability Model			
	Guide				Guide			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
ML ESG $_{t-1}$	3.615***				0.1320***			
	(3.409)				(2.901)			
ML E $_{t-1}$		1.634***				0.0640**		
		(2.808)				(2.457)		
ML S $_{t-1}$			2.678**				0.0871	
			(2.286)				(1.448)	
ML G $_{t-1}$				1.598**				0.0565*
				(2.233)				(1.927)
InstHold	0.006*	0.006*	0.006*	0.006*	0.0002*	0.0002*	0.0002*	0.0002*
	(1.674)	(1.676)	(1.646)	(1.688)	(1.759)	(1.746)	(1.758)	(1.780)
Analysts	0.588***	0.581***	0.596***	0.595***	0.0226***	0.0225***	0.0226***	0.0228***
	(3.650)	(3.598)	(3.696)	(3.697)	(3.863)	(3.842)	(3.857)	(3.894)
AFE	0.000	0.000	0.000	0.000	−0.0000	−0.0000	−0.0000	−0.0000
	(0.129)	(0.159)	(0.205)	(0.180)	(−0.803)	(−0.790)	(−0.770)	(−0.788)
Size	−0.253***	−0.252***	−0.253***	−0.248***	−0.0082***	−0.0082***	−0.0080***	−0.0080***
	(−3.240)	(−3.219)	(−3.225)	(−3.157)	(−3.280)	(−3.277)	(−3.215)	(−3.188)
BM	0.014	0.010	0.017	0.014	−0.0016	−0.0016	−0.0015	−0.0015
	(0.117)	(0.085)	(0.140)	(0.120)	(−0.786)	(−0.813)	(−0.738)	(−0.775)
AgeFirm	−0.064***	−0.064***	−0.063***	−0.064***	−0.0009***	−0.0010***	−0.0009***	−0.0009***
	(−9.554)	(−9.521)	(−9.496)	(−9.517)	(−7.703)	(−7.730)	(−7.684)	(−7.674)
Turnover	−0.022***	−0.022***	−0.023***	−0.023***	−0.0008***	−0.0008***	−0.0008***	−0.0008***
	(−2.708)	(−2.716)	(−2.783)	(−2.742)	(−3.367)	(−3.390)	(−3.450)	(−3.382)

(*continued on next page*)

Table 4 (*continued*)

Panel B	Logit				Linear Probability Model			
Beta	0.330***	0.330***	0.330***	0.326***	0.0100**	0.0100**	0.0099**	0.0099**
	(2.636)	(2.641)	(2.645)	(2.605)	(2.028)	(2.021)	(1.997)	(2.006)
Ivol	−12.291**	−12.154**	−12.317**	−12.192**	−0.0567	−0.0549	−0.0574	−0.0539
	(−2.275)	(−2.258)	(−2.272)	(−2.256)	(−0.434)	(−0.421)	(−0.440)	(−0.413)
BMdisp	−0.003	−0.003	−0.003	−0.003	−0.0000	−0.0000	−0.0000	−0.0000
	(−1.466)	(−1.453)	(−1.473)	(−1.509)	(−1.137)	(−1.192)	(−1.187)	(−1.141)
Litigation	−0.128	−0.117	−0.120	−0.101	0.0053	0.0055	0.0059	0.0062
	(−0.483)	(−0.445)	(−0.451)	(−0.383)	(0.210)	(0.218)	(0.232)	(0.245)
ManHold	−0.021*	−0.021*	−0.020	−0.021	−0.0007	−0.0007	−0.0006	−0.0007
	(−1.684)	(−1.657)	(−1.568)	(−1.607)	(−1.562)	(−1.540)	(−1.510)	(−1.539)
Intercept	−1.399*	−1.281*	−1.167	−1.328*	0.0127	0.0151	0.0190	0.0148
	(−1.959)	(−1.806)	(−1.624)	(−1.838)	(0.669)	(0.795)	(1.030)	(0.803)
Fisc qtr FE	X	X	X	X	X	X	X	X
Ind FE	X	X	X	X	X	X	X	X
N	50,700	50,700	50,700	50,700	53,895	53,895	53,895	53,895
Pseudo R^2 / R^2	0.1939	0.1933	0.1925	0.1927	0.0670	0.0669	0.0665	0.0667

also find a positive relation between institutional holdings, analysts' following and the likelihood of earnings guidance (information demand hypothesis), and a negative relation between firm size, age, stock trading volume turnover and the likelihood of earnings guidance.

We next test whether managers' voluntary earnings guidance decreases information asymmetry by linking management earnings forecasts to proxies of information asymmetry: *Spread*, *logAIM*, *AFDsip*, and *EarnAnnVol*. We follow Nagar et al. (2019, section 4.4), Schoenfeld (2017), and Hao and Pham (2023) and build a recursive structural equations model (or path model) of ESG disclosure score, earnings guidance, and information asymmetry (Greene, 2002, p. 397).

The recursive model involves three steps. First, we empirically model earnings guidance as a function of ESG disclosure and controls (see Eq. (3)). Second, we empirically model information asymmetry (*Spread*,

Table 5
ESG disclosure, earnings guidance, and information asymmetry.
This table analyzes the effect of ESG disclosure on information symmetry using data measured at quarterly intervals. We estimate the effect of ESG disclosure on information asymmetry by first regressing earnings guidance on the ESG disclosure score and controls in Table 4. In this table, we then recursively regress information asymmetry proxies: Spread, logAIM, AFDisp and EarnAnnVol on earnings guidance, the ESG scores, and controls. We account for the determinants of information asymmetry and earnings guidance by including contemporaneous control variables (similar to those in Table 3) and lagged control variables (similar to those in Table 4, respectively. The OLS models control for year and industry fixed effects; standard errors are clustered by firm, and t-stats are reported below the coefficients. *, ** and *** indicate statistical significance at less than the 10 %, 5 %, and 1 % levels, respectively.

	Bloom ESG				ML ESG			
	Spread	logAIM	AFDisp	EarnAnnVol	Spread	logAIM	AFDisp	EarnAnnVol
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Bloom ESG it	0.0014***	0.0003***	0.3574	−0.0095				
	(3.422)	(2.605)	(1.138)	(−1.016)				
ML ESG it					0.0419**	0.0014	19.4674**	1.343***
					(1.979)	(0.233)	(2.316)	(2.849)
Guide it	0.0035	0.0008	−9.147***	0.8157***	0.0040	0.0025	−8.478***	0.625***
	(0.451)	(0.377)	(−5.072)	(2.643)	(0.455)	(0.590)	(−7.153)	(3.472)
InstHold it	−0.0016***	−0.0003***	0.0131	0.0083***	−0.0016***	−0.0004***	0.0092	0.005***
	(−5.713)	(−3.007)	(0.334)	(3.166)	(−6.013)	(−4.752)	(0.342)	(2.682)
Analysts it	0.0107	0.0058**	−0.0096	0.2661**	0.0126**	0.0059***	−1.3277	0.225**
	(1.642)	(2.204)	(−0.006)	(2.303)	(2.328)	(3.572)	(−1.072)	(2.471)
Size it	−0.0346***	−0.0063***	−3.5856***	−0.4942***	−0.040***	−0.007***	−3.059***	−0.578***
	(−7.750)	(−3.973)	(−3.689)	(−7.499)	(−8.607)	(−6.219)	(−4.665)	(−10.882)
B/M it	0.0179***	0.0020	7.9584***	−0.3397***	0.0342***	0.0059***	7.2664***	−0.244***
	(2.624)	(0.838)	(3.586)	(−3.088)	(3.855)	(3.156)	(3.263)	(−3.320)
AgeFirm it	−0.0001	−0.0000	−0.0375	−0.0214***	0.0004***	0.0001*	0.0231	−0.025***
	(−0.592)	(−0.606)	(−0.773)	(−7.778)	(3.593)	(1.877)	(0.592)	(−10.687)
Turnover it	−0.0030***	−0.0009***	0.4199***	0.0390***	−0.005***	−0.001***	0.2619***	0.036***
	(−3.979)	(−3.076)	(2.987)	(4.033)	(−8.188)	(−6.150)	(2.934)	(5.784)
Intercept	0.4356***	0.0692***	−9.2914	14.9610***	0.8234***	0.0468***	44.3472**	10.467***
	(8.275)	(3.914)	(−0.633)	(18.174)	(11.889)	(3.118)	(2.219)	(15.681)
Lagged (t-1) ESG score, and Firm-Level Controls from Table 4	X	X	X	X	X	X	X	X
Industry FE	X	X	X	X	X	X	X	X
Year FE	X	X	X	X	X	X	X	X
N	27,062	27,062	27,062	27,062	53,802	53,802	53,802	53,802
R^2	0.275	0.084	0.049	0.437	0.423	0.104	0.038	0.409
Indirect effect of ESG disclosure (through Guide) on information asymmetry guide coeff. × Bloom ESGt-1 coeff. From Table 4A, Column 5								
	0.000005	0.000001	−0.0119***	0.0011***				
	(0.452)	(0.379)	(−3.295)	(2.256)				
Indirect effect of ESG disclosure (through Guide) on information asymmetry guide coeff. × ML ESGt-1 coeff. From Table 4B, Column 5								
					0.0005	0.0003	−1.1191	0.0824
					(0.196)	(0.273)	(−1.241)	(1.017)

logAIM, *AFDsip*, and *EarnAnnVol*) as a function of earnings guidance, ESG disclosure, and controls (see Eq. (4)). Third, we use the results from the first two steps to compute the indirect effect of ESG disclosure on information asymmetry, i.e., the extent to which earnings guidance offsets (or does not offset) increased information asymmetry due to ESG disclosure. The exclusion restriction is that the error terms are uncorrelated in Eqs. (3) and (4), which implies that there is no factor that affects both earnings guidance and information asymmetry that is not accounted for by the industry-year-fixed effects or the control variables. Similar to asserting the exogeneity of an instrument, the exclusion restriction is untestable (Roberts & Whited, 2013). The equations for this procedure are as follows:

$$Guide_{it} = \alpha_0 + \alpha_1 ESG_{it-1} + \theta X_{it-1} + \delta_t + \gamma_i + \varepsilon_{it}, \quad (3)$$

$$IA_{it} = \beta_0 + \beta_1 ESG_{it} + \beta_2 Guide_{it} + \pi Z_{it} + \beta_3 ESG_{it-1} + \theta X_{it-1} + \eta_t + \gamma_i + \nu_{it}, \quad (4)$$

where the dependent variables *Guide* is 1 if firm *i* issues guidance in quarter *t* and 0 otherwise, in linear probability model and *IA* is one of four proxies of information asymmetry: bid-ask *Spread*, logarithm of the Amihud illiquidity measure (*LogAIM*), and analysts' forecast dispersion (*AFDisp*) *volatility* in market response to earnings announcements (*EarnAnnVol*). Index *i* represents the firm, index *t* represents the year-quarter, and θ and π represent vectors of firm-level control variables. Note that since β_2's value in Eq. (4) depends on ε_{it} in Eq. (3), we must include in Eq. (4) the full Eq. (3) of ESG_{it-1} and θX_{it-1}. Quarter (Year) fixed effects, represented by δ_t (η_t), control for year trends, and industry-specific unobserved characteristics are accommodated through an industry-fixed effect γ_i. ε_{it} is the error term, with standard errors clustered at the firm level.

We expect that earnings guidance will impact information asymmetry relatively quickly in an active market. Thus, in Table 5 we regress quarterly firm-level *Spread*, *logAIM*, *AFDsip*, and *EarnAnnVol* on contemporaneous quarterly firm-level earnings guidance and ESG disclosure measures (Bloomberg ESG disclosure score (columns (1) through (4)) and ML ESG disclosure score (columns (5) through (8)) with industry-year-fixed effects and controls. As noted above, we include the full set of lagged regressors from Table 4, as well as contemporaneous controls for *Spread*, *logAIM*, *AFDsip*, and *EarnAnnVol*.

To compute the indirect effect of Bloomberg ESG disclosure (through earnings guidance) on *Spread*, *logAIM*, *AFDsip*, and *EarnAnnVol*, we multiply the earnings guidance regressor coefficients in Table 5, Columns (1) through (4) by the Bloomberg ESG regressor coefficient in Table 4 Panel A, Column 5 (linear probability model). The resulting products are 0.00005 for *Spread* (0.0035*0.0013; insignificant), 0.000001 for *logAIM* (0.0008*0.0013; insignificant), negative – 0.0119 for *AFDisp* (– 9.147*0.0013; 1 % level), and 0.0011 for *EarnAnnVol* (0.8157*0.0013; 1 % level). We use the delta method to compute standard errors for these products as $\widehat{s}_{\beta_a\beta_b} = \sqrt{s^2_{\beta_a}\beta^2_b + s^2_{\beta_b}\beta^2_a}$ (Krull & MacKinnon, 2001; Sobel, 1987). We calculated the indirect effect of ESG disclosure measured with Machine Learning ESG score the same way by multiplying the earnings guidance regressor coefficients in Table 5, Columns (5) through (8) by the ML ESG regressor coefficient in Table 4 Panel B, Column 5 (linear probability model). The indirect effect coefficients in this specification are statistically insignificant. Our results indicate that earnings guidance partially offsets ESG disclosure effect on information asymmetry only measured with Analysts' Forecast Dispersion (*AFDisp*) proxy but does not mitigate the effect of ESG disclosure on information asymmetry surrounding a firm proxied with our other measures.

4.4. Robustness test: Bloomberg ESG disclosure initiation and the likelihood of earnings guidance

While our main empirical model in Eq. (2) runs with lagged explanatory variables of ESG disclosure scores and controls for fiscal quarter and industry effects, some endogeneity concerns between ESG disclosure and earnings guidance may still be present. To address them, we use the quasi-exogenous shock of Bloomberg ESG disclosure coverage of the firms in the sample (Chen & Xie, 2022). A start of ESG disclosure scores' reporting by Bloomberg is not a firm-initiated event and therefore should be independent of earnings guidance practices. To implement the test, we apply multivariate logit and ordered logit models (accounting for the precision of guidance with the ordered logit) as in eq. (2). Specifically, we use the following model estimated with the control for the industry and fiscal quarter fixed effects with standard errors clustered at the firm level:

$$Guide_{it} = \beta_0 + \beta_1 D\_Bloom_{it-1} + \beta_2 Treat_{it-1} + \theta X_{it-1} + \delta_t + \gamma_i + \varepsilon_{it} \quad (5)$$

where the dependent variable *Guide* is 1 if firm *i* issues guidance in quarter *t* and 0 otherwise, in the logit model, and equals 1 if the firm issues open interval earnings guidance for quarter *t*, 2 if the firm issues range guidance for quarter *t*, 3 if the firm issues point guidance for quarter *t*, and 0 otherwise, ordered logit model.[8] The main explanatory variables are *D_Bloom*, which is an indicator variable that equals 1 if a firm has Bloomberg ESG disclosure score coverage, and 0 otherwise, and *Treat*, which is an indicator variable that equals 1 if a company had Blomberg ESG disclosure initiated during or before the sample period and 0 otherwise. We are interested in the coefficient β_1 that captures the effect of Bloomberg ESG disclosure coverage on the propensity score of earnings guidance issuance. A positive coefficient would confirm our earlier finding that ESG disclosure is positively associated with earnings guidance. Coefficient β_2 on *Treat* variable captures the effect on firms from having Bloomberg ESG disclosure coverage over the sample periods versus control firms that never receive Bloomberg ESG disclosure score coverage. Other explanatory variables included in vector ***X*** that contain lagged firm- and quarter-specific characteristics are *InstHold*, *Analysts*, *AFE*, *Size*, *BM*, *AgeFirm*, *Turnover*, *Beta*, *IVol*, *MTB*, *Litigation*, and *ManHold*. Year and fiscal quarter fixed effects, represented by δ_t, control for yearly and quarterly macro-trends, and industry-specific unobserved characteristics are accommodated through an industry fixed effect, γ_i. ε_{it} is the error term, with standard errors clustered at the firm level.

Before running the difference-in-difference test, we check for the parallel trend assumption that the treatment group (firms getting Bloomberg ESG coverage) and the control group (firms not receiving initiation of Bloomberg ESG coverage) exhibit a parallel trend before the treatment event. We compare changes in earnings guidance issuance between treatment and control groups in the period before the initiation of Bloomberg ESG coverage using STATA code estat ptrends. We find no significant difference in the earnings guidance trend between the two groups prior to the event (untabulated).

Table 6 reports the results of Bloomberg coverage initiation on earnings guidance frequency and quality. Confirming the results in Section 4.3, we observe a positive coefficient on *D_Bloom*, indicating that initiation of the coverage by Bloomberg ESG disclosure scores for the treated firms is positively associated with the likelihood of earnings guidance. Thus, firms that have been added to the Bloomberg ESG disclosure coverage provide more earnings guidance in comparison to those before being covered by Bloomberg score. At the same time, firms that are in the control group, i.e., firms not being added to the Bloomberg coverage of ESG disclosure scores have a higher propensity score of earnings guidance in comparison to treated firms, probably due to higher firm information asymmetry within the control group. We perform the test within a reduced sample that has firms with initiation of Bloomberg ESG coverage within the study period (Columns (1)), and exclude firms that always had coverage by Bloomberg ESG scores within

[8] Ordered logit regression results are similar and untabulated.

Table 6
Effect of Bloomberg ESG disclosure coverage on the likelihood of voluntary Earnings Guidance – difference in difference test.
This table presents the results of the analysis of the likelihood of management earnings guidance issue from logit regressions, where the dependent variable (*Guide*) equals 1 if the firm issues earnings guidance for quarter *t* and 0 otherwise. The main explanatory variables are *D_Bloom*, which is an indicator variable equal 1 if firm has Bloomberg disclosure score coverage and 0 otherwise over the sample period, and *Treat*, which is an indicator variable equal 1 if company had Blomberg ESG disclosure initiated during or before the sample period and 0 otherwise. Column (1) is the logit model for the sample that excludes firms 'always treated', i.e., those that have Bloomberg ESG disclosure coverage for the whole sample period; column (2) is the logit model for the whole sample of firms. All other control variables are defined in Section 3. All regressions control for fiscal quarter, and industry fixed effects. Robust standard errors are clustered by firm, and t-stats are reported below the coefficients. *, **, and *** indicate significance at the 10 %, 5 %, and 1 % levels, respectively.

	Guide	Guide
	New Bloomberg coverage	New and prior Bloomberg coverage
	(1)	(2)
D_Bloom	1.439***	1.320***
	(3.458)	(3.220)
Treat	−1.784***	−1.800***
	(−4.262)	(−4.317)
InstHold	0.004*	0.004*
	(1.835)	(1.782)
Analysts	0.467***	0.495***
	(2.853)	(3.122)
AFE	0.000	0.000
	(0.618)	(0.364)
Size	−0.203**	−0.202**
	(−2.348)	(−2.521)
BM	0.131	0.036
	(1.395)	(0.302)
AgeFirm	−0.075***	−0.065***
	(−10.035)	(−10.125)
Turnover	−0.021***	−0.024***
	(−2.618)	(−2.996)
Beta	0.334**	0.309**
	(2.553)	(2.538)
Ivol	−14.127***	−13.605***
	(−2.703)	(−2.640)
BMdisp	−0.003	−0.003
	(−1.370)	(−1.496)
Litigation	−0.056	−0.103
	(−0.206)	(−0.400)
ManHold	−0.026	−0.021
	(−1.550)	(−1.551)
Intercept	−0.683	−0.667
	(−0.960)	(−1.003)
Fiscal qtr FE	X	X
Industry FE	X	X
N	45,078	51,637
Pseudo R^2	0.2349	0.2191

the sample period, i.e., those that did not experience initiation of coverage. Full sample results are in column (2). The reduced sample result for *D_Bloom* variable is economically stronger but is about the same for *Treat* variable as for the full sample.

4.5. ESG disclosure and market response to earnings guidance

A higher level of integrity and a focus on social responsibility should also be positively assessed by the market. For example, Hsu et al. (2019) find that involvement in CSR activities signals management integrity and indicates firms' disclosure quality; therefore, adverse CSR performance negatively affects stock price reactions surrounding announcements of earnings and management earnings forecasts. Wong and Zhang (2022) claim that there are financial incentives for companies to carefully monitor a good corporate reputation related to ESG matters. The authors observe a significant adverse stock market reaction to negative ESG media, indicating a potential need to incorporate ESG factors into modern portfolio management models. Moreover, companies involved in ESG activities have a higher sensitivity to earnings surprises in the 3-day period surrounding earnings announcements. Additionally, in the 60-day period following the earnings announcement, socially engaged companies are characterized by less pronounced earnings surprises and post-announcement drift (PEAD) or reversals (Bartov & Li, 2015; DeLisle et al., 2022).

As companies involved in ESG activities are less likely to manipulate earnings and are keen on reporting in a more conservative and accurate way, information signals produced by earnings guidance issued by companies that are more involved in ESG disclosure are expected to be stronger and have less post-announcement drift than the earnings guidance signals of companies with less involvement in ESG disclosure. Additionally, higher ESG disclosure scores may be associated with more information asymmetry and, as a result, more surprises around informative events, such as earnings guidance.

To empirically test whether a firm's ESG disclosure affects share price response to guidance announcements, we employ an OLS regression model on panel data with the industry and fiscal quarter fixed effect in subsamples of guidance classified as positive, negative, or neutral news. The model is as follows:

$$CAR_{i,t} = \beta_0 + \beta_1 ESG_{it-1} + \theta X_{it-1} + \delta_t + \gamma_i + \varepsilon_{it}, \quad (5)$$

where the dependent variable is the market response to guidance release measured by the signed cumulative abnormal return calculated over (−1, +1) days windows around company-issued guidance, CAR for firm *i* in quarter *t*. The main explanatory variable, *ESG*, is one of the following firm ESG disclosure proxies: the *Bloomberg ESG* disclosure score and its three pillars (*Bloomberg E*, *Bloomberg S*, and *Bloomberg G*), and the ML ESG disclosure score and its three pillars (*ML E*, *ML S*, and *ML G*). Other explanatory variables included in vector ***X*** that contain lagged firm- and quarter-specific characteristics are *InstHold*, *Analysts*, *AFE*, *Size*, *BM*, *AgeFirm*, *Turnover*, *Beta*, *IVol*, *MTB*, *Litigation*, and *ManHold*. In addition, we control for guidance characteristics, such as *G_Duration*, which is the number of days between the first day management issued guidance for quarterly earnings and the corresponding fiscal quarter end earnings announcement day; *Precision,* which equals three if the company issued a point estimate, two if a range estimate was issued, and one if the guidance was provided as an open interval. Fiscal quarter fixed effects, represented by δ_t, control for quarterly macro-trends, and industry-specific unobserved characteristics are accommodated through an industry fixed effect, γ_i. ε_{it} is the error term with standard errors clustered at the firm level.

Table 7 presents the results of the effect of ESG disclosure on the market response to earnings guidance. We do not find any significant relation between the Bloomberg ESG scores and the market response to any type of earnings guidance defined as positive, negative, or neutral. The ML scores also have no relation with the market response to positive, negative, or neutral earnings guidance.[9] Overall, the results indicate that the market does not have a clear view of how to interpret information about ESG disclosure's effect on the informativeness of earnings guidance.

5. Conclusions

Firms may use different ways of disclosing information to stakeholders to build a more transparent image and decrease information asymmetry. Building on stakeholders' theory, we consider the relation between involvement in ESG disclosure and earnings guidance through the information asymmetry link.

Our findings suggest that ESG disclosure is positively associated with

[9] We repeat the tests with CAR (−5,+5) and CAR (−10,+10) and find the same results as with the shorter window. The results are untabulated.

Table 7
Market response to earnings guidance.
This table presents results from ordinary least squares regression analysis of CAR(−1,+1) days around earnings guidance issuances and other control variables using a sample of guiding firm-quarters. The main explanatory variable is one of the proxies for firm ESG disclosure: Bloomberg (Panel A), and machine learning (ML) (Panel B) ESG scores and the three pillars. All control variables are defined in Section 3. All regressions control for fiscal quarter and industry fixed effects. Robust standard errors are clustered by firm, and t-stats are reported below the coefficients. *, **, and *** indicate significance at the 10 %, 5 %, and 1 % levels, respectively.

Panel A	Positive Guidance				Negative Guidance				Neutral Guidance			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Bloom_ESG	0.097				-0.087				-0.057			
	(0.855)				(−1.382)				(−0.707)			
Bloom_E		0.056				-0.062*				-0.020		
		(1.017)				(−1.758)				(−0.548)		
Bloom_S			0.042				-0.046				-0.062	
			(0.343)				(−0.887)				(−0.844)	
Bloom_G				0.149				-0.014				0.005
				(0.802)				(−0.129)				(0.036)
InstHold	0.059	0.061	0.057	0.054	0.035	0.036	0.035	0.039	-0.063*	-0.061*	-0.065*	-0.060*
	(1.133)	(1.150)	(1.092)	(1.045)	(1.225)	(1.286)	(1.217)	(1.360)	(−1.852)	(−1.791)	(−1.868)	(−1.750)
Analysts	4.004**	3.895*	4.074**	4.112**	3.469*	3.610*	3.412*	3.450*	-0.984	-0.987	-1.111	-1.057
	(2.015)	(1.959)	(2.056)	(2.067)	(1.822)	(1.912)	(1.778)	(1.771)	(−0.679)	(−0.678)	(−0.771)	(−0.731)
AFE	0.185	0.191	0.180	0.177	0.042***	0.041***	0.043***	0.043***	0.067	0.090	0.052	0.096
	(0.609)	(0.630)	(0.577)	(0.569)	(2.777)	(2.699)	(2.858)	(2.802)	(0.079)	(0.107)	(0.061)	(0.116)
Size	0.036	0.086	0.210	0.258	0.680	0.668	0.589	0.405	1.215*	1.112*	1.290*	1.002*
	(0.025)	(0.064)	(0.138)	(0.195)	(0.899)	(0.917)	(0.775)	(0.565)	(1.888)	(1.813)	(1.837)	(1.676)
BM	3.010	2.939	3.455	3.528	-0.670	-0.576	-0.826	-0.960	-0.312	-0.403	-0.200	-0.534
	(0.691)	(0.685)	(0.796)	(0.842)	(−0.273)	(−0.235)	(−0.333)	(−0.391)	(−0.192)	(−0.247)	(−0.121)	(−0.324)
AgeFirm	0.302**	0.304**	0.302**	0.289**	-0.067	-0.069	-0.067	-0.068	-0.077	-0.077	-0.080*	-0.081*
	(2.289)	(2.291)	(2.265)	(2.181)	(−1.441)	(−1.471)	(−1.423)	(−1.444)	(−1.635)	(−1.626)	(−1.678)	(−1.724)
Turnover	-0.321	-0.323	-0.319	-0.322	-0.424**	-0.427**	-0.422**	-0.425**	0.017	0.018	0.025	0.015
	(−1.364)	(−1.371)	(−1.359)	(−1.376)	(−2.400)	(−2.424)	(−2.374)	(−2.380)	(0.110)	(0.113)	(0.162)	(0.092)
Beta	4.760**	4.805**	4.699*	4.633*	-2.020	-1.961	-2.019	-1.931	0.510	0.582	0.423	0.658
	(2.041)	(2.057)	(1.983)	(1.936)	(−1.292)	(−1.272)	(−1.272)	(−1.230)	(0.305)	(0.349)	(0.251)	(0.393)
Ivol	607.399*	609.344*	608.252*	609.869*	38.784	32.632	41.539	34.568	236.233*	233.999*	240.757*	232.901*
	(1.938)	(1.953)	(1.934)	(1.949)	(0.344)	(0.289)	(0.368)	(0.313)	(1.930)	(1.917)	(1.968)	(1.902)
BMDisp	2.448	2.446	2.515	2.422	1.244	1.264	1.146	1.031	-0.856	-0.882	-0.812	-0.929
	(0.866)	(0.856)	(0.890)	(0.864)	(0.871)	(0.885)	(0.803)	(0.722)	(−0.561)	(−0.575)	(−0.536)	(−0.604)
Precision	1.174	1.164	1.159	1.069	-0.974	-1.058	-0.788	-0.645	-1.518	-1.514	-1.485	-1.495
	(0.394)	(0.387)	(0.393)	(0.365)	(−0.409)	(−0.443)	(−0.335)	(−0.272)	(−0.875)	(−0.877)	(−0.853)	(−0.875)
Gduration	0.025	0.024	0.026	0.026	-0.003	-0.003	-0.004	-0.004	0.001	0.001	0.001	0.001
	(0.949)	(0.909)	(0.972)	(0.978)	(−0.192)	(−0.161)	(−0.224)	(−0.234)	(0.048)	(0.053)	(0.040)	(0.053)
Intercept	-51.35***	-48.48***	-50.11***	-61.92***	-19.057**	-22.279**	-20.705**	-19.063	0.408	-0.631	-0.870	-0.185
	(−2.893)	(−2.732)	(−2.770)	(−2.731)	(−2.076)	(−2.468)	(−2.270)	(−1.372)	(0.039)	(−0.060)	(−0.081)	(−0.012)
Fisc qtr FE	X	X	X	X	X	X	X	X	X	X	X	X
Ind FE	X	X	X	X	X	X	X	X	X	X	X	X
N	151	151	151	151	486	486	486	486	432	433	433	433
R^2	0.2542	0.2549	0.2517	0.2530	0.2157	0.2170	0.2143	0.2135	0.1112	0.1118	0.1132	0.1113

Panel B	Positive Guidance				Negative Guidance				Neutral Guidance			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
ML_ESG	-1.697				-2.968				11.035*			
	(−0.160)				(−0.407)				(1.919)			
ML_E		-5.659				-0.659				4.620		
		(−1.097)				(−0.171)				(1.531)		

(*continued on next page*)

Table 7 (*continued*)

Panel B	Positive Guidance				Negative Guidance				Neutral Guidance			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
ML_S			-1.575				-11.363				5.070	
			(−0.113)				(−1.166)				(0.740)	
ML_G				6.191				0.851				6.520*
				(0.874)				(0.145)				(1.750)
InstHold	0.031	0.031	0.031	0.034	0.013	0.013	0.012	0.013	0.022*	0.021*	0.021*	0.022**
	(1.321)	(1.325)	(1.344)	(1.418)	(0.938)	(0.940)	(0.836)	(0.933)	(1.942)	(1.859)	(1.851)	(2.014)
Analysts	-0.490	-0.453	-0.488	-0.450	-0.843	-0.847	-0.811	-0.850	-0.580	-0.598	-0.594	-0.552
	(−0.493)	(−0.454)	(−0.489)	(−0.460)	(−1.186)	(−1.193)	(−1.138)	(−1.194)	(−1.095)	(−1.132)	(−1.128)	(−1.037)
AFE	0.050	0.053	0.050	0.067	0.033	0.033	0.034	0.033	-0.224**	-0.224**	-0.223**	-0.225**
	(0.129)	(0.138)	(0.131)	(0.173)	(1.010)	(1.005)	(1.019)	(1.001)	(−2.073)	(−2.077)	(−2.040)	(−2.071)
Size	1.156**	1.157**	1.151*	1.108*	1.266***	1.262***	1.271***	1.258***	0.968***	0.978***	0.988***	0.969***
	(1.990)	(1.972)	(1.965)	(1.920)	(3.353)	(3.337)	(3.396)	(3.352)	(3.363)	(3.408)	(3.450)	(3.361)
BM	-1.732	-1.739	-1.737	-1.741	-0.228	-0.220	-0.262	-0.218	0.256	0.228	0.270	0.263
	(−0.936)	(−0.939)	(−0.934)	(−0.948)	(−0.297)	(−0.286)	(−0.341)	(−0.282)	(0.307)	(0.272)	(0.324)	(0.316)
AgeFirm	0.201**	0.198*	0.202**	0.198*	-0.128***	-0.127***	-0.129***	-0.127***	-0.048	-0.048	-0.051	-0.050
	(2.004)	(1.963)	(2.002)	(1.925)	(−3.302)	(−3.296)	(−3.324)	(−3.284)	(−1.533)	(−1.534)	(−1.613)	(−1.609)
Turnover	-0.089	-0.089	-0.089	-0.089	-0.250***	-0.249***	-0.246***	-0.249***	-0.071	-0.070	-0.070	-0.071
	(−1.112)	(−1.110)	(−1.112)	(−1.111)	(−4.462)	(−4.447)	(−4.408)	(−4.443)	(−1.612)	(−1.588)	(−1.604)	(−1.614)
Beta	-0.027	-0.081	-0.032	-0.099	-1.104	-1.093	-1.141*	-1.086	-0.150	-0.176	-0.180	-0.188
	(−0.026)	(−0.078)	(−0.031)	(−0.096)	(−1.614)	(−1.601)	(−1.674)	(−1.591)	(−0.301)	(−0.353)	(−0.358)	(−0.379)
Ivol	351.294***	349.233***	351.098***	348.240***	−113.03**	−113.118**	−114.417**	−113.372**	99.700***	99.695***	97.181***	98.235***
	(5.572)	(5.524)	(5.588)	(5.458)	(−1.992)	(−1.993)	(−2.018)	(−1.996)	(2.677)	(2.674)	(2.616)	(2.648)
BMdisp	-0.020	-0.020	-0.020	-0.021	0.010	0.009	0.011	0.009	0.010	0.013	0.015	0.008
	(−0.771)	(−0.797)	(−0.778)	(−0.796)	(0.384)	(0.358)	(0.451)	(0.335)	(0.603)	(0.855)	(0.919)	(0.515)
Precision	1.013	0.985	1.015	1.004	-0.910	-0.911	-0.937	-0.914	0.196	0.210	0.179	0.182
	(0.923)	(0.902)	(0.925)	(0.914)	(−0.957)	(−0.957)	(−0.989)	(−0.960)	(0.279)	(0.297)	(0.252)	(0.260)
Gduration	0.000	-0.000	0.000	0.001	0.025**	0.025**	0.025**	0.025**	0.012	0.012	0.011	0.012
	(0.020)	(−0.004)	(0.028)	(0.074)	(2.393)	(2.382)	(2.389)	(2.385)	(1.119)	(1.095)	(1.074)	(1.120)
Intercept	-12.065**	-11.619*	-12.129**	-12.561**	-1.238	-1.440	-1.208	-1.644	-10.992***	-10.362***	-9.941***	-10.89***
	(−1.970)	(−1.899)	(−2.015)	(−2.077)	(−0.228)	(−0.265)	(−0.223)	(−0.306)	(−2.993)	(−2.740)	(−2.625)	(−2.958)
Fisc qtr FE	X	X	X	X	X	X	X	X	X	X	X	X
Ind FE	X	X	X	X	X	X	X	X	X	X	X	X
N	655	655	655	655	1845	1845	1845	1845	1997	1997	1997	1997
R^2	0.1575	0.1585	0.1575	0.1584	0.1594	0.1593	0.1601	0.1593	0.0349	0.0341	0.0333	0.0346

information asymmetry, confirming the findings of previous studies observing high divergence and disagreement between ESG scores (e.g., Berg et al., 2022; Christensen et al., 2022; Kimbrough et al., 2022). We find that increased ESG disclosure, measured with Bloomberg and machine learning ESG disclosure scores, is positively related to the probability and informativeness of earnings guidance. The result holds in a robustness test of the quasi-exogenous event of the initiation of the Bloomberg ESG disclosure coverage of firms. Our results also suggest that ESG disclosure and earnings guidance may have different roles and effects on the firm's information asymmetry. The primary benefit of issuing voluntary earnings guidance is information asymmetry reduction, but these activities come with costs, such as legal liabilities (Kasznik, 1999), proprietary costs (Verrecchia, 1983), and higher auditing fees (Krishnan et al., 2012). However, companies experiencing increased information asymmetry, in part due to ESG activity disclosures, might opt for more frequent and precise voluntary earnings guidance as a strategy to mitigate information gaps arising from diverse sources and types of information.

We also find that the market does not link disclosed information about ESG to information released in earnings guidance. This finding may be explained by the fact that market participants do not clearly understand how to interpret information about ESG disclosure due to the high diversity of ESG scores provided by public ranking agencies and lack of shared understanding regarding ESG metrics (Berg et al., 2022; Christensen et al., 2022; Kimbrough et al., 2022; Serafeim & Yoon, 2022).

Our paper contributes to previous research on the methods of information disclosure to achieve information asymmetry reduction (e.g., Cho et al., 2013; Cui et al., 2018; Diamond & Verrecchia, 1991; Verrecchia, 2001). We empirically show that ESG disclosure increases information asymmetry, possibly due to a lack of agreement on how to interpret disclosed ESG information. The findings of this study shed light on ways different types of information disclosure affect information asymmetry, specifically, on the role of involvement in ESG disclosure on voluntary earnings guidance practices.

As we observe a positive relation between ESG disclosure and the probability of issuing earnings guidance, our results provide potentially useful insights and implications for policymakers, regulators, and companies that pay specific attention to socially responsible practices. The conclusions in this paper add to the debate regarding the need for clear and formalized guidelines for sustainability reporting and disclosure through the establishment of proper standards for sustainability (Kimbrough et al., 2022) that should help decrease disagreement and improve a common understanding regarding ESG information (Christensen et al., 2022). The role of ESG disclosure in affecting information asymmetry might be of high interest to the SEC and the European Commission. The idea of mandatory ESG disclosure of high quality is that it gives incentives to companies to incorporate sustainability aspects into their operations, so investors, consumers, policy makers, and other stakeholders can monitor and evaluate the non-financial performance of the disclosing companies. The results of this study are in line with the requirement of the Corporate Sustainability Reporting Directive (CSRD) that entered into force on January, 5th, 2023, which requires a broad set of large companies, as well as listed SMEs to disclose information on social, environmental, and governance issues with the first reports to be published in 2025.[10]

The outcomes of this study suggest that better standards for mandatory ESG disclosure are important, as they might decrease disagreement about disclosed ESG information, which might lead to a decrease in information asymmetry and further reduction in the need for voluntary earnings guidance, which is subject to the cost–benefit tradeoff for companies. Therefore, building on Christensen et al. (2022) and Kimbrough et al. (2022), we claim that an increase in ESG disclosure across firms does not help resolve ESG disagreement, and therefore, there is a need for common norms and practices that should be developed by policymakers to explain what constitutes good and bad ESG performance. We suggest that it is not the quantity but the quality and understandability of ESG disclosure (Haji et al., 2022) that might be an important factor for a decrease in information asymmetry.

Our study provides new insights into the determinants of voluntary earnings guidance. Although rules and regulations are being formed on how ESG practices should be reported, earnings guidance is still a voluntary event. Thus, the rules set for ESG disclosure affect earnings guidance practices. The results of this paper also shed light on how involvement in ESG activities influences market reactions to information events, confirming that investors pay attention to the ESG agenda while trading stocks; however, they may distinguish between ESG performance and ESG disclosure. In conclusion, as the intersection of ESG disclosure and earnings guidance continues to evolve, this study underscores the critical need for a nuanced understanding of their synergistic effects on market dynamics and firm transparency, calling for further scholarly exploration and informed policy-making to navigate these complex terrains.

Data availability

No

Appendix A. Appendix

A.1. Description of the machine learning procedure

Word embedding language models (Mikolov et al., 2013) offer one solution to build more objective word dictionaries. This approach uses neural networks to model words with low-dimensional vectors (usually 100–300 elements) that preserve their semantic information. These neural networks are trained with large-scale textual data sets, in our case 10-K forms. After training with a large textual corpus, closely associated words and phrases – discussed and referred to in a similar context in 10-Ks – have similar vector representations, i.e., they are close to each other in the vector space. Thus, words like *profit* and *earnings* have similar vectors in that space. The word embeddings approach is advantageous compared to the traditional word dictionary approach because it quantifies semantics. It represents words and phrases in such a manner as how humans understand them. Thus, the vectors possess detailed information about the nuances and relationships of words and are not just measures of the co-occurrence of words (Li et al., 2021). Therefore, the word embedding approach allows us to build powerful measures to estimate different concepts from 10-K forms, in our case ESG, using a few seed words for each ESG pillar and collecting words closest to them in the word embedding vector space (Table A.1). With this data-driven objective approach, we can create an extensive, high-quality dictionary from 10-K forms that correctly considers the context of words and phrases in that disclosure type (Bhatia et al., 2021).

A few papers in business disciplines have already used word embeddings successfully. Li et al. (2021) built a word embedding model using 209,480

[10] Earlier, publicly listed companies in EU had to report on ESG issues in line with the Directive, 2014/95/EU starting from the year 2018, covering fiscal year 2017.

earnings call transcripts to measure corporate culture. They demonstrate how their approach is much more detailed and powerful than those used by previous research. Bhatia et al. (2021) use a word embedding model to identify leadership traits and demonstrate how their model is on par with human judgment, demonstrating the powerfulness of this approach. Harrison et al. (2019) use a word embedding model to measure CEOs' big five personality traits. They validate their CEO personality measure using the previously explored links between CEOs' big five traits and strategic change and show that their word embedding model has a strong convergent and discriminant validity.

We follow the approach of Li et al. (2021) in building our word embedding model.[11] The training data consists of 460,000 10-K forms from the Edgar database (https://www.sec.gov/edgar), which we first preprocess and then feed to the neural network to create the word embeddings. We start by cleaning up all the unnecessary information from the forms, such as HTML tags, and keeping only textual information. However, when creating word embeddings, nothing should be removed from the textual part, which is often done with the traditional bag-of-words approach. We do not want to break the flow of the narrative, which is what we specifically try to model with our word embeddings model. Thus, we proceed by replacing numbers with a specific symbol (#), as numbers do not contain useful information for us and just decrease the quality of the representations. For the same reason, we do not remove short and long words, and keep all stopwords.

Next, we identify named entities from the corpus to improve the quality of the representations. For that, we use a pre-trained deep learning model from the spaCy library (www.spacy.io). Different types of named entities are replaced with a phrase NER_ (type of entity). We use the same model to recognize *noun chunks* from the text. The noun chunks are phrases that include nouns and words related to those nouns. Li et al. (2021) argue that phrases are crucial when creating high-quality measures from text using word embeddings. Noun chunks created by a deep learning model are also of much higher quality than bigrams/trigrams, which are solely based on the co-occurrence of words. To the best of our knowledge, Routledge et al. (2018) is the first paper in business research that used a deep learning model to recognize noun chunks from the text.

In our final step, we use a neural network model (word2vec by Mikolov et al. (2013)) to learn the vector representations for the dictionary words and phrases found in the 10-K forms. The Gensim library (radimrehurek.com/gensim/) in Python contains an implementation of the word2vec model, which we use to build our measure. Word2vec learns optimal representations for predicting the surrounding words using the central word (i.e., it uses the skip-gram approach). We then proceed by finetuning our trained model with only 10-K forms from a specific industry to get industry-specific weightings for the words/phrases that we use as our measure.

We use our model to estimate how environmental, social and governance discussions are disclosed in 10-K forms. We use five seed words for each pillar of ESG. The seed words for environmental are *sustainability, climate change, global warming, emissions*, and *our environment*. Similarly, the seed words for social are *our people, our culture, our values*, *dedication*, and *teamwork*, and the seed words for governance are *our governance*, *our structure, practices, our principles,* and *board oversight.* Using five seed phrases instead of just the name of a pillar, we wanted to verify the quality of our measure. For example, using only *social* as a seed word for the social pillar of ESG would have included aspects to the measure that we think do not belong there. Next, we infer the 100 closest words/phrases for each pillar's seed words. Finally, the relative occurrence of these words in 10-K forms is our measure for each pillar of ESG.

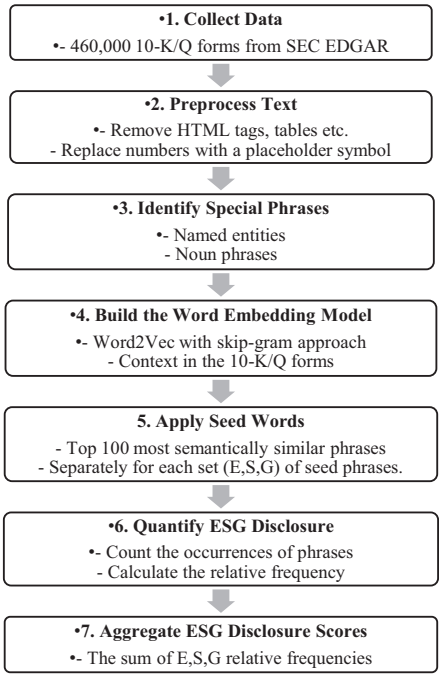

Fig. A.1 The figure summarized the steps of the machine learning procedure used to extract information about companies' ESG disclosure.

[11] Figure A.1. summarized the steps of the machine learning procedure used to extract information about companies' ESG disclosure.

Table A.1 Machine learning seed words for word vector space.
The table lists 100 closest phrases to the five seed words in the word vector space for each pillar.

Environmental pillar	global_warming; food_security; air_quality; global_issues; water_scarcity; the_planet; energy_policy; industry; landscape; environments; health; resource; dynamics; conservation; geologic; sustainability; environmental; climate; ecological; consumer; maritime; atmospheric; regulatory; legislative; agriculture; air; hygiene; technological; political; marketplace; geotechnical; agriculturally; bioforensic; fisheries; ecosystems; smarter_cities; metallurgical; envir; circuit; logistical; modernization; atomic; cloud_activity; water_quality; public_safety; arctic; the_mega_trends; extreme_designs; forestry; oil_processes; shale; geospatial; intelligent; food_safety; fire_prevention; ecobiotic; people_safety; our_nation; safety_health; wildlife; ecology; airline; geopolitical; enduring; our_environment; mexico_oil; biodiversity; change_policies; critical_health; nuclear_safety; animal_habitat; standards; environmentally; fuel_leaks; haze; temperature; risk_technology; ecosystem; to_long_term; our_bamboo; agricultural; geophysically; infrastructures; automation; gas_shale; electrical; air_land; chemical; an_environment; innovative; geographic; deepwater; logistics; shale_project; dynamic_nature; geologic_basins; innovation; meteorological; polluted_waters; farm_efficiency
Social pillar	Leadership; excellence; creativity; our_people; our_values; wellness; inspiring; the_culture; our_culture; literacy; compassion; embraces; teamwork; our_world; the_habits; innovation; ethnic; learning; mentoring; inspires; individuality; coaching; kindness; mutual_respect; this_spirit; personal_growth; mindfulness; philosophy; wellbeing; glamour; better_sleep; sustainability; fostering; favorite; well_being; talent; celebrating; society; popular_culture; vocabulary; championing; these_tenets; the_theme; welcoming; thoughts; moments; thrives; strong_culture; fun; workplace; wisdom; passion; lifelong; empowerment; philanthropy; unwavering; volunteerism; the_passion; early_learning; inclusivity; empathy; fosters; religion; business_skills; success_stories; behavioral; teacher; embracing; nurtures; online_teaching; admiration; your_leadership; humor; visual; intellectually; reading_skills; an_open_culture; living_life; everyone; adventure; fluency; school_spirit; lifestyles; multicultural; foster; our_innovation; comprehension; our_teams; spirited; the_vision; health; mentorship; respectful; warm_inviting; enthusiasm; strong_leaders; intelligence; teams; team_building; motivational
Governance pillar	our_governance; our_ethics; oversight; risk_management; organizational; internal_audit; independence; governance; committees; oversees; nominating; accountability; corporate; employee_code; board; the_governance; auditing; audit_committee; supervisory; policymaking; practices; leadership; board_affairs; conduct_policy; business_ethics; governance_risk; director_code; regulatory; boards; the_committees; the_board_role; our_committees; human_resource; advisory; compliance_code; legislative; conduct_code; auditors; ethics_code; human_capital; corporate_risk; risk_control; board_oversight; human_resources; clear_roles; conduct_board; board_processes; risk_committee; integrity; analogous_rules; our_code; the_oversight; insider; policies; standards; policy_code; risk_oversight; board_role; rule_changes; guidelines; frameworks; ceo_report; communications; strong_program; ethical_conduct; these_key_risks; defined_roles; oversee; audit_functions; supervision; good_governance; securities_code; committees_code; insider_filings; business_code; ethics_board; varying_norms; communication; officers_code; our_codes; our_oversight; risk_governance; ethics; directorates; risk_policies; key_policies; public_affairs; disciplinary; joint_code; oversight_rules; overseeing; security_policy; directors_codes; the_management; policy_plans; reporting; board_structure; risk_compliance; formal_policies; risk_assessment

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