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ESG rating disagreement and analyst forecast quality

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ABSTRACT

This study examines the effect of ESG rating disagreement on analysts' earning forecast using a sample consisting of ESG ratings of Chinese A-share listed companies from 2015 to 2021 by six rating agencies including RSK, SynTao Green Finance, Hexun, Bloomberg, Huazheng and Wind. We find that greater ESG rating disagreement is linked to increased forecast error and dispersion among analysts. The mechanism test confirms that ESG rating disagreement exacerbates information asymmetry, leading to greater forecast inaccuracies and dispersion. Further analysis reveals that the negative impact of ESG rating disagreement is more pronounced in companies with worse information environments, while experienced and diligent analysts, alongside star analysts, can mitigate such negative effect of rating disagreement. Our findings contribute to the literature on ESG rating disagreement from an analyst's perspective, providing empirical evidence from emerging capital market about the economic consequences of ESG rating disagreement.

1. Introduction

The growing impact of climate change and environmental issues on the global economy and society has underscored the importance of sustainability, thus drawing significant attention from governments worldwide. In 2020, the Chinese government announced the "dual carbon goal" of striving to achieve the carbon peak by 2030 and carbon neutrality by 2060, reflecting a major strategic move towards economic structural transformation and sustainable development. ESG, as a primary index for assessing sustainable development (Baker, Boulton, Braga-Alves, & Morey, 2021), emphasizes enterprise efforts in environmental protection, social responsibility fulfillment, and governance enhancement. This aligns closely with China's "high-quality development strategy" and "dual carbon goal". Therefore, ESG is attached to great importance by the capital market, enterprises, and government. By mid-2023, approximately 34% of A-share listed companies had disclosed their ESG reports for 2022. The State-owned Assets Supervision and Administration Commission (SASAC) required that central state-owned enterprises should explore and establish a sound ESG system in 2022; the China Securities Regulatory Commission (CSRC) also released a new scheme emphasizing the establishment of a sound sustainable information disclosure framework and the promotion of green economic and social development. Additionally, the allocation of capital resources also increasingly hinges on companies' ESG performance. From the borrowing side, firm's financing costs are significantly affected by ESG performance (Gigante & Manglaviti, 2022). From the lending side, banks have incorporated ESG into their lending decision and even practice ESG washing (Huang, Bui, Hsu, & Lin, 2024).

However, due to the lack of unified ESG disclosure and evaluation standards, great differences in data sources, evaluation indicators and rating methods among various rating agencies result in rating disagreement of the same listed company (Berg, Koelbel, & Rigobon, 2022; Chatterji, Durand, Levine, & Touboul, 2016). Such divergence in ESG ratings introduces additional costs in information acquisition and processing, and may potentially mislead information users, thus reducing resource allocation efficiency in the capital market (Christensen, Serafeim, & Sikochi, 2022). As demonstrated by Brandon, Krueger, and Schmidt (2021) and Avramov, Cheng, Lioui, and Tarelli (2021), ESG rating disagreement is correlated to higher stock returns and less green investment. A practical example is that 37 Interactive

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Entertainment, a well-known Chinese network technology company rated diversely by several ESG rating agencies during the past few years, was rated as AA by MSCI-ESG in 2023; however, two months before the rating, the company announced to be investigated by the China Securities Regulatory Commission for suspected violation of information disclosure, and its stock hit a limit down afterwards. In brief, the risk of ESG rating disagreement has been confirmed mainly on the investors' side. Therefore, it is still worth figuring out what impact ESG rating disagreement has on other information users in the capital market, such as the sell side. Besides, considering that such divergence is contributed by various rating measurements, ESG disagreement may have potential informativeness. In specific, information users may acquire more dimensions to deepen their understanding of companies and ultimately help their investment decisions. To examine such possibility, we analyze the impact of ESG rating disagreement on financial analysts' earning forecast quality.

Financial analysts, as key intermediaries in the capital market, forecast enterprise future earnings and provide valuable reference to investment. Previous studies hold that information environment and information quality are among the key factors affecting analyst prediction accuracy (Hilary & Shen, 2013). Analysts' information sets consist of public and private, financial and non-financial information. Among these, ESG ratings, serving as a significant non-financial metric which offers an evaluation of a company's performance in environmental, social, and governance, can supplement financial information. Therefore, analysts are likely to incorporate ESG into their earnings forecasts (Christensen, Hail, & Leuz, 2021; Hsu, Koh, Liu, & Tong, 2019). Ideally, rating agencies are expected to create and disseminate high-quality ESG ratings and scores in capital markets out of the incentives of industry competition and reputation costs (Tsang, Tracie, & Cao, 2022). However, the existence of rating disagreement among agencies diminishes the information quality. As studies pointed out, ESG rating disagreement essentially signifies uncertainty and risk (Avramov et al., 2021), which will increase the information processing cost and difficulty, and reduce analyst forecast accuracy and consistency (Griffin, Neururer, & Sun, 2020). In this case, it is an interesting topic whether ESG ratings and rating disagreements could provide analysts with incremental information to enhance earning forecast quality and direct more capital towards sustainable development. If not, then whether ESG rating disagreement aggravates the information redundancy and increases analysts' costs of information collection and processing? Whether it impairs the accuracy of analysts' earning forecast and lowers the efficiency of market resource allocation?

We examine such an effect of China's capital market for several reasons. Firstly, there may exist a greater divergence of ESG ratings in China than in other developed markets. As Luo, Yan, and Yan (2023) pointed out, most domestic rating agencies began the rating report only after 2010, and the Ministry of Finance first encouraged the voluntary disclosure of ESG information of listed companies only in 2016. Therefore, the emerging filed are likely to produce greater differences. Secondly, the coexistence of both domestic and international rating agencies in China's capital market may further exacerbate rating disagreement. The difference in founding principles, purpose, legal status, and legal origin among domestic and international rating agencies strongly influence their preference and weight in ESG evaluation (Eccles and Stroehle, 2018; Liang & Renneboog, 2017). For instance, Chen, Li, Mao, & Yoon (2022) found that Chinese local raters capture more factors of social and governance issues which require an understanding of local context, and thus they outperform international raters in making more risk-relevant ratings. Finally, the possible severer adverse impact of ESG rating disagreement caused by immature China's stock market makes it necessary to discuss how financial analysts deal with such divergence. It is known that Chinese stock traders consist of a large proportion of retail investors who are often irrational, overconfident, and knowledge-unequipped. ESG rating disagreement impairs their sentiment and ultimately decreases the stock returns (Wang, Wang, Dong, & Wang, 2024). To avoid further negative consequences, the important precondition is to explore what impact ESG disagreement has on sophisticated information users, such as financial analysts. If analysts are disturbed by such divergence, then the retail investors could be puzzled to a greater degree.

Using ESG ratings of China A-share listed companies from 2015 to 2021 by six ESG rating agencies, including RSK, SynTao Green Finance, Hexun, Bloomberg, Huazheng and Wind, we construct a sample consisting of 11,081 firm-year observations from 2673 unique companies. The regression results show that ESG rating disagreement can significantly increase analyst forecast error and dispersion. Mechanism test shows that ESG rating disagreement amplifies information asymmetry and then impairs forecast quality. Further analysis reveals that this relation is more pronounced in companies with worse information environments. However, if analysts have stronger ability and more information channels, they can mitigate the negative interference of ESG rating disagreement.

We contribute to the literature in the following three aspects. Firstly, we contribute to the literature on ESG rating disagreement. Since ESG rating disagreement has been brought into focus only in recent times, there are few relevant studies yet. Previous research has mainly focused on the consequences of ESG disclosure rather than ESG rating disagreement. For example, Dhaliwal, Li, Tsang, and Yang (2011) find that ESG disclosure is positively related to firm value. Chen and Xie (2022) document that ESG disclosure has a favourable effect on corporate financial performance. Atif and Ali (2021) show that firms with more ESG disclosure have lower default risk. Unlike the above studies, we examine the impact of ESG rating disagreement on information users in the capital market from the perspective of analyst forecast. The results show that ESG rating disagreement amplifies information asymmetry and thus indicate that ESG ratings may be helpful but the informativeness is limited. Secondly, we provide empirical evidence about the impact of ESG disagreement from emerging capital market. Most literature is based on Western mature capital markets to investigate the contributions to ESG rating disagreement (Christensen et al., 2022; Kimbrough, Wang, Wei, & Zhang, 2024), while this paper sheds a new light on economic consequences of ESG rating disagreement from China, one of the emerging capital markets, and supports the concept that ESG rating disagreement exerts "noise effect". Therefore, our study helps to deepen the understanding of ESG ratings and rating disagreement. Thirdly, we also add to the study of factors affecting analyst forecast quality. Prior research discussed how analysts' work experience, industry expertise, information quality and information property influence the prediction accuracy and dispersion (Cohen, Frazzini, & Malloy, 2010; Jennings, 1987; Kumar, 2010). Although several studies have pointed out that non-financial information such as CSR disclosure (Dhaliwal et al., 2011), mandatory R&D disclosure (Liu, Huang, Chen, & Chan, 2023) and ESG practices (Bernardi & Stark, 2018; Cui, Jo, & Na, 2018) could influence analyst forecast quality, there is little focus on how ESG rating disagreement affects it. And this study complements that ESG rating disagreement is another factor that impairs analyst forecast accuracy.

2. Literature review

2.1. ESG rating disagreement

Academic exploration into ESG rating disagreement bifurcates into two primary areas: the contributions and the economic consequences. The origin of ESG rating divergence is fundamentally attributed to the absence of a uniform framework regarding the disclosure and assessment of firms' ESG performance. Firstly, there exists a notable lack of consensus among raters concerning the scope, measurement, and weighting of evaluation (Berg et al., 2022; Chatterji et al., 2016), which results in inconsistencies. Particularly when firms disclose more ESG information, agencies are more likely to employ divergent metrics for

Table 1
Descriptive statistics.

Type	Variables	N	Mean	St.Dev	Min	Median	Max
Independent variable	Disagreement	11,081	0.466	0.162	0.063	0.470	0.876
Dependent variables	FERR	11,081	2.231	4.697	0.007	0.684	32.590
	FDIS	11,081	1.256	2.533	0.036	0.441	18.329
Control variables	SOE	11,081	0.357	0.479	0.000	0.000	1.000
	Balance	11,081	0.245	0.119	0.029	0.234	0.538
	InShr	11,081	0.470	0.247	0.011	0.497	0.927
	Dual	11,081	0.270	0.444	0.000	0.000	1.000
	Indep	11,081	0.377	0.054	0.333	0.364	0.571
	Analyst	11,081	2.070	0.897	0.693	2.079	3.892
	Big4	11,081	0.083	0.276	0.000	0.000	1.000
	Opac	11,081	0.694	0.646	0.000	1.000	3.000
	ROA	11,081	0.050	0.058	−0.158	0.044	0.229
	Lev	11,081	0.438	0.190	0.069	0.434	0.864
	Size	11,081	22.834	1.286	20.423	22.634	26.668
	BM	11,081	0.605	0.270	0.114	0.587	1.187
	Epsv	11,081	0.458	0.343	0.028	0.377	1.933
	Age	11,081	2.978	0.277	1.946	2.996	3.989

Notes: This table reports the number, mean, standard deviation, median, minimum and maximum values of all variables used in our regression.

assessing companies' performances, thus causing further disagreement rather than convergence. Additionally, individual raters' subjective interpretations, influenced by their varying information processing abilities, experiences, preferences, and habits, further exacerbate the disparity in ESG ratings for the same entity (Christensen et al., 2022). Secondly, the different disclosure policies and report contents of listed companies themselves contribute to this rating divergence. Kimbrough et al. (2024) demonstrate that voluntary ESG report publication by companies, particularly those adhering to advanced Global Reporting Initiative (GRI) standards and featuring third-party attestations, tend to mitigate rating disagreement. However, reports characterized by more positive tones or a great number of sticky words can amplify these disagreements. As for the possible economic consequences of ESG rating divergence, the hidden uncertainty will lead investors to demand heightened risk compensation and reduce their investment in risky assets, ultimately elevating firms' capital costs (Avramov et al., 2021; Brandon et al., 2021).

2.2. Analyst forecast

The quality of analyst forecast is predominantly influenced by the information environment. Analysts utilize both financial and non-financial information from enterprises (Dhaliwal et al., 2011), whose quantity and quality significantly impact forecast quality (Liu et al., 2023). Previous studies have extensively examined the effects of financial information disclosure on forecast outcomes. For instance, analyst forecast accuracy increases when enterprises provide higher-quality financial information (Lambert, Leuz, & Verrecchia, 2007), make more forward-looking disclosure (Bozzolan, Trombetta, & Beretta, 2009), employ the top-5 accounting firms (De Franco, Kothari, & Verdi, 2011), and issue management forecasts (Hilary & Shen, 2013). Analyst forecast dispersion is negatively related to annual financial report (Hope, 2003), forward-looking disclosure (Beretta & Bozzolan, 2008; Vanstraelen, Zarzeski, & Robb, 2003), and monthly earnings disclosure (Tsao, Lu, & Keung, 2016).

Non-financial disclosures, such as CSR reports (Dhaliwal et al., 2011), CSR narratives (Muslu, Mutlu, Radhakrishnan, & Tsang, 2019), and mandatory R&D disclosures (Liu et al., 2023), similarly aid analysts in enhancing earnings forecast quality by providing implemented information (Amir & Lev, 1996). Moreover, more ESG practices and quality disclosures have been shown to diminish errors and dispersion in analyst forecasts (Bernardi & Stark, 2018; Cui et al., 2018). However, negative ESG events, which spark social controversies, amplify enterprise uncertainty, thus complicating analysts' predictive tasks and leading to increased forecast errors (Schiemann & Tietmeyer, 2022). Beyond the information environment, analyst attributes also significantly influence forecast quality. Factors such as professional capability (Dang, Foerster, Li, & Tang, 2021), industry expertise (Jacob, Lys, & Neale, 1999), work experience (Hilary & Shen, 2013), reputation (Meng, 2015), and social networks (Cohen et al., 2010) are beneficial to enhancing earnings forecast accuracy. While variations of weights that analysts use (Lang, Lins, & Miller, 2003; Lang & Lundholm, 1996), forecast models (Green & Armstrong, 2015), the quantity of private information (Byard, Li, & Yu, 2011), and the ability of information utilization (Indjejikian, 1991) among analysts can increase forecast dispersion.

3. Hypothesis development

ESG as a summary measure of non-financial performance (Christensen et al., 2022), is closely linked to firm value and future risk (Khan, Yoon, & Serafeim, 2016; Amel-Zadeh & Serafeim, 2017), thus is incorporated in financial analysts earning forecast (Hsu et al., 2019). ESG rating agencies evaluate how well companies are managing environmental, social, and governance risks and opportunities based on various rating metrics and measurements, to meet the capital market's demand for ESG information and sustainable investment (Christensen et al., 2022; MSCI, 2018). Ideally, competition and reputational incentives should motivate raters to provide and disseminate high-quality ESG ratings, offering incremental information to the market (Tsang et al., 2022). However, in China's emerging market, ESG rating has only been introduced in recent years and a standardized ESG disclosure framework has not yet been formed. This makes ESG information less formalized than financial data, leading to greater rating divergence among agencies (Christensen et al., 2022). Based on the above analysis, the impact of ESG rating disagreement on analyst earning forecast is unclear. Therefore, this paper aims to explore the dual aspects of ESG rating disagreement's impact: the noise effect and the informative effect.

3.1. Noise effect of ESG rating disagreement

Firstly, ESG ratings, as less formalized information, can exacerbate information asymmetry in markets with poor information environments. Disagreement among independent rating agencies might signal uncertainty and ambiguity in a firm's information disclosure. As highlighted by Dimson, Marsh, and Staunton (2020), missing data is one of the contributions to rating divergence. For example, when a company does not reveal certain metrics, some ESG rating agencies assume the worst and choose to assign a score of zero, while other raters may impute a score reflecting the performance of peer companies that disclose such metrics, which leads to rating disagreement. Missing or ambiguous information increases the complexity and incomparability of information,

Table 2
Regression analysis of ESG disagreement on analyst forecast quality.

	(1)	(2)	(3)	(4)
	FERR	FDIS	FERR	FDIS
Disagreement	1.552***	1.580***	0.675*	0.536***
	(5.655)	(10.712)	(1.940)	(2.866)
SOE			−0.226*	−0.060
			(−1.916)	(−0.952)
Balance			−0.393	−0.264
			(−1.029)	(−1.284)
InShr			−1.376***	−0.635***
			(−5.971)	(−5.127)
Dual			−0.164	−0.063
			(−1.584)	(−1.135)
Indep			1.398*	0.732*
			(1.728)	(1.683)
Analyst			−0.009	−0.014
			(−0.134)	(−0.412)
Big4			0.180	0.123
			(1.041)	(1.317)
Opac			0.309***	0.165***
			(4.076)	(4.037)
ROA			−16.405***	−8.889***
			(−17.033)	(−17.171)
Lev			−0.317	−0.337**
			(−0.997)	(−1.971)
Size			−0.127*	−0.004
			(−1.874)	(−0.120)
BM			−0.311	−0.546***
			(−1.120)	(−3.663)
Epsv			0.668***	0.398***
			(4.860)	(5.387)
Age			0.152	0.004
			(0.879)	(0.045)
Constant	1.509***	0.520***	5.333***	1.864**
	(11.144)	(7.147)	(3.756)	(2.441)
Industry FE	NO	NO	YES	YES
Year FE	NO	NO	YES	YES
N	11,081	11,081	11,081	11,081
Adjusted-R^2	0.003	0.010	0.070	0.076

Notes: This table provides empirical results of the regression model with ESG rating disagreement (*Disagreement*) as the independent variable, and forecast error and forecast dispersion as the dependent variables respectively. Columns (1) and (2) presents the process of incorporating control variables. All of the continuous variables are winsorized at the 1% and 99% levels. T values are in parentheses below the coefficient values. Significance levels at $p <$ 10%, 5% and 1%, one-tailed, are indicated by *, ** and ***, respectively.

which raises analysts' information processing costs and difficulty. Furthermore, ESG rating disagreement, essentially representing uncertainty (Avramov et al., 2021), to a certain extent, signifies operational risks in a firm. Great operational risks may deviate firm's business performance from the average level of industry, and then increase the uncertainty of its earnings, which may also introduce information redundancy and complicate analysts' forecasting tasks. The negative effect on analyst forecast could be explained from two aspects. On the one hand, higher information processing cost reduces the forecast accuracy (Griffin et al., 2020). On the other hand, puzzling and incomparable information decreases the general quality of public information sets and then leads to greater forecast dispersion (Brown, Richardson, & Schwager, 1987).

Secondly, analysts' limited attention (Hirshleifer & Teoh, 2003) makes it challenging for them to optimally process large volumes of incomparable information, which potentially impairs analyst forecast ability. As Christensen et al. (2022) pointed out, the lack of common sense on how to measure and what to measure gives raters more opportunities to create different interpretations. Although the diverse assessment methods of rating agencies do provide multiple dimensions to understand firms' ESG performance, the non-negligible fact is that those ratings are subjective interpretations from agencies. Since analysts have limited attention, it is hard to distinguish the material part of hidden information behind the ratings and to decide which rating to incorporate into the earnings forecast. In this case, ESG rating disagreement imposes more costs of information processing on financial analysts and could result in higher forecast errors. Similarly to how rating agencies deal with the raw ESG information, analysts can rely on the rule of thumb and subjective judgment when constructing their information sets and choosing different forecast models. As a result, the forecast dispersion will be amplified. Therefore, we propose our second hypothesis:

H1a: ESG rating disagreement will increase analyst forecast errors and forecast dispersion.

3.2. Informative effect of ESG rating disagreement

The informativeness of ESG rating disagreement is rooted in the hidden information behind factors that contribute to such disagreement. Firstly, since ESG disclosure standards are absent, different ESG disclosures lead to ESG rating disagreement to some degree (Christensen et al., 2022). The incomplete disclosure system in China, characterized by non-mandatory ESG disclosure and the lack of a standardized disclosure framework, allows companies to report ESG information diversely. This may potentially enrich analysts' information sources. Secondly, the variety in assessment scopes, metrics, and weights among ESG rating agencies results in rating disagreement (Berg et al., 2022). Such diversified analyzing perspectives actually represent the expertise of ESG rating agencies. Therefore, those measurements can provide analysts with multiple dimensions for interpreting firm-level ESG practices, which may complement financial data. The enrichment of information sets helps analysts deepen their understanding of firms' operational performance and future risks, which benefits forecast accuracy. Also, ESG ratings as a kind of typical public information decrease the information asymmetry among analysts, which may reduce the forecast dispersion. Thus, we propose our first hypothesis:

H1b: ESG rating disagreement will reduce analyst forecast errors and forecast dispersion.

4. Data and research design

4.1. Sample and data

The sample contains ESG rating scores of Chinese A-share listed companies from 6 rating agencies including RSK, SynTao Green Finance, Hexun, Bloomberg, Huazheng, and Wind. To ensure that all rating scores from different agencies are in the same scoring range, we apply the following steps. First, RSK updated its evaluation system in 2019, so some companies were measured twice by both the old and new versions and received two ratings in that year ultimately. We then keep the score calculated by the updated measurement and drop the other one. Besides, different from the old measurement system which scores companies from 0 to 100, the new one does it from 0 to 10. So, we multiply the scores of 2019–2021 by 10. Second, the rating range of Hexun is from −20 to 100. Therefore, we plus 20 to all scores from Hexun and then scale them by 100 to make ratings range from 0 to 100. Third, we also multiply scores of Wind by 10 because Wind takes 0–10 as their rating range. Moreover, we exclude companies in the financial industry or with an ST (Special Treatment) and *ST (Delisting Risk) mark, because they are abnormal and may disturb the empirical results. Our sample begins in 2015, the first year that SynTao Green Finance reported ESG ratings, and ends in 2021 considering the data availability at the time we constructed the sample. Following Christensen et al. (2022), we require each firm-year with two or more ratings. Finally, our sample consists of 11,081 firm-year observations from 2673 unique companies. The financial data of listed companies are from the CSMAR database. All of the continuous variables are winsorized at the 1% and 99% levels to mitigate the influence of outliers.

Table 3
Robustness checks.

Panel A	Control analyst characteristics	Extended sample of 2012–2021	Firm fixed effect	Firm-clustered standard errors				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	FERR	FDIS	FERR	FDIS	FERR	FDIS	FERR	FDIS
Disagreement	0.703*	0.466**	0.697**	0.549***	0.866*	0.710***	0.675*	0.536**
	(1.777)	(2.196)	(2.205)	(3.144)	(1.699)	(2.610)	(1.677)	(2.404)
SOE	−0.140	−0.027	−0.085	−0.016	−0.086	−0.115	−0.226*	−0.060
	(−1.044)	(−0.381)	(−0.812)	(−0.276)	(−0.207)	(−0.520)	(−1.788)	(−0.908)
Balance	−0.768*	−0.530**	−0.450	−0.299	−1.052	0.012	−0.393	−0.264
	(−1.771)	(−2.276)	(−1.323)	(−1.589)	(−1.059)	(0.023)	(−0.894)	(−1.051)
InShr	−1.541***	−0.701***	−1.430***	−0.675***	−3.063***	−1.676***	−1.376***	−0.635***
	(−5.919)	(−5.014)	(−6.948)	(−5.934)	(−4.275)	(−4.385)	(−5.503)	(−4.624)
Dual	−0.205*	−0.081	−0.084	−0.028	−0.186	−0.161*	−0.164	−0.063
	(−1.739)	(−1.285)	(−0.885)	(−0.528)	(−1.048)	(−1.700)	(−1.443)	(−1.022)
Indep	2.042**	0.990**	0.883	0.604	0.655	0.528	1.398	0.732
	(2.275)	(2.054)	(1.200)	(1.484)	(0.432)	(0.652)	(1.600)	(1.548)
Analyst	−0.056	−0.046	0.031	−0.017	0.347***	0.108**	−0.009	−0.014
	(−0.769)	(−1.179)	(0.544)	(−0.534)	(3.765)	(2.200)	(−0.122)	(−0.381)
Big4	0.031	0.022	−0.058	−0.013	1.181**	0.700***	0.180	0.123
	(0.152)	(0.203)	(−0.368)	(−0.150)	(2.386)	(2.650)	(1.007)	(1.221)
Opac	0.347***	0.175***	0.267***	0.141***	−0.157	−0.068	0.309***	0.165***
	(4.033)	(3.777)	(3.882)	(3.693)	(−1.609)	(−1.308)	(3.719)	(3.558)
ROA	−9.744***	−4.963***	−17.870***	−10.386***	−15.034***	−7.871***	−16.405***	−8.889***
	(−11.681)	(−11.082)	(−19.887)	(−20.918)	(−12.061)	(−11.834)	(−12.650)	(−12.635)
Lev	−0.222	−0.321*	−0.664**	−0.471***	−3.093***	−1.684***	−0.317	−0.337
	(−0.631)	(−1.701)	(−2.329)	(−2.985)	(−4.605)	(−4.699)	(−0.811)	(−1.473)
Size	−0.165**	−0.008	−0.045	0.050	0.634***	0.389***	−0.127*	−0.004
	(−2.159)	(−0.187)	(−0.741)	(1.505)	(2.987)	(3.439)	(−1.790)	(−0.116)
BM	0.399	−0.199	−0.236	−0.534***	1.029**	0.011	−0.311	−0.546***
	(1.302)	(−1.212)	(−0.936)	(−3.839)	(2.188)	(0.043)	(−1.009)	(−3.295)
Epsv	0.781***	0.494***	0.651***	0.373***	0.455***	0.302***	0.668***	0.398***
	(5.642)	(6.646)	(5.315)	(5.520)	(2.660)	(3.305)	(3.981)	(4.049)
Age	−0.017	−0.076	0.047	−0.057	−1.659	−1.432*	0.152	0.004
	(−0.086)	(−0.705)	(0.320)	(−0.709)	(−1.025)	(−1.658)	(0.764)	(0.037)
Gender	−0.225*	0.003						
	(−1.790)	(0.050)						
Degree	0.203*	−0.006						
	(1.648)	(−0.090)						
Experience	−0.007*	−0.002						
	(−1.846)	(−0.838)						
ForecastNumber	−0.001	0.000						
	(−0.239)	(0.035)						
FollowingNumber	−0.002	−0.000						
	(−0.257)	(−0.115)						
Constant	5.926***	1.825**	4.160***	1.102	−5.675	−2.307	5.333***	1.864**
	(3.671)	(2.105)	(3.314)	(1.589)	(−0.867)	(−0.661)	(3.611)	(2.325)
Industry FE	YES	YES	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES	YES	YES
N	8759	8759	14,611	14,611	10,758	10,758	11,081	11,081
Adjusted-R^2	0.062	0.065	0.068	0.082	0.387	0.399	0.070	0.076

Panel B	Alternative definition of independent variables	Alternative definition of dependent variables				
	(1)	(2)	(3)	(4)	(5)	(6)
	FERR	FDIS	FERR	FDIS	FERR_D	FDIS_D
Disagreement_Ind	0.882*	0.495**			1.601***	0.364**
	(1.895)	(1.980)			(4.242)	(2.344)
Disagreement_avr			0.018*	0.010*	−0.860***	−0.310***
			(1.950)	(1.929)	(−6.736)	(−5.916)
SOE	−0.230*	−0.063	−0.229*	−0.063	1.031**	−0.336**
	(−1.954)	(−1.002)	(−1.943)	(−0.991)	(2.489)	(−1.970)
Balance	−0.422	−0.292	−0.429	−0.297	−2.031***	−0.706***
	(−1.107)	(−1.425)	(−1.126)	(−1.448)	(−8.128)	(−6.871)
InShr	−1.365***	−0.628***	−1.366***	−0.629***	−0.051	−0.080*
	(−5.925)	(−5.071)	(−5.928)	(−5.075)	(−0.454)	(−1.730)
Dual	−0.164	−0.064	−0.164	−0.064	0.591	0.469
	(−1.581)	(−1.145)	(−1.583)	(−1.148)	(0.672)	(1.297)
Indep	1.367*	0.716	1.368*	0.717*	0.099	0.102***
	(1.688)	(1.645)	(1.690)	(1.649)	(1.434)	(3.592)
Analyst	−0.014	−0.016	−0.014	−0.016	−0.175	−0.140*
	(−0.213)	(−0.464)	(−0.217)	(−0.460)	(−0.930)	(−1.805)
Big4	0.166	0.105	0.165	0.103	0.970***	0.235***
	(0.963)	(1.126)	(0.958)	(1.112)	(11.781)	(6.930)
Opac	0.314***	0.169***	0.311***	0.167***	−13.044***	−0.220
	(4.135)	(4.132)	(4.094)	(4.093)	(−12.478)	(−0.511)

(continued on next page)

Table 3 (*continued*)

Panel A	Control analyst characteristics	Extended sample of 2012–2021	Firm fixed effect	Firm-clustered standard errors		
ROA	−16.492***	−9.056***	−16.549***	−9.099***	0.933***	0.641***
	(−17.303)	(−17.674)	(−17.503)	(−17.900)	(2.708)	(4.521)
Lev	−0.307	−0.341**	−0.314	−0.347**	−0.100	0.081***
	(−0.963)	(−1.993)	(−0.986)	(−2.028)	(−1.363)	(2.659)
Size	−0.113*	0.008	−0.105	0.012	6.237***	3.053***
	(−1.680)	(0.218)	(−1.556)	(0.343)	(20.700)	(24.645)
BM	−0.350	−0.581***	−0.364	−0.589***	1.039***	0.290***
	(−1.266)	(−3.909)	(−1.318)	(−3.964)	(6.961)	(4.724)
Epsv	0.667***	0.398***	0.663***	0.396***	0.136	−0.069
	(4.855)	(5.387)	(4.822)	(5.355)	(0.721)	(−0.886)
Age	0.152	0.005	0.152	0.004	0.959	−1.878***
	(0.880)	(0.051)	(0.875)	(0.047)	(0.622)	(−2.961)
Constant	4.969***	1.651**	4.827***	1.585**	(1)	(2)
	(3.473)	(2.147)	(3.351)	(2.047)	FERR_D	FDIS_D
Industry FE	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES
N	11,081	11,081	11,081	11,081	11,194	11,194
Adjusted-R^2	0.070	0.076	0.070	0.076	0.208	0.187

Notes: This table reports the results of robustness checks. In panel A, columns (1) and (2) show the results after including more analyst-related variables in control variables; columns (3) and (4) report the results of regression where the sample has been extended to 2012–2021; columns (5) and (6) show the results of firm-fixed effect; columns (7) and (8) comprise the results of regression with firm-clustered standard error. Panel B columns (1)–(4) and (5)–(6) report the regression results of alternative independent variables and dependent variables respectively. In columns (1) and (2), *Disagreement* has been replaced by a industry-adjusted disagreement (*Disagreement_Ind*), and in columns (3) and (4) we use the *Disagreement_Avr* as independent variable, which is the method of Avramov et al. (2021). In columns (5) and (6), we alternate the dependent variables by using stock price *Pt* as denominator. All the results in the above tests are robust. Significance levels at p < 10%, 5% and 1%, one-tailed, are indicated by *, ** and ***, respectively.

4.2. Variables

4.2.1. Dependent variables

The dependent variables are analyst forecast error (*FERR*) and analyst forecast disagreement (*FDIS*). We follow Shi, Song, Xu, and Xu (2023) to construct *FERR* as the absolute value of the mean errors for forecasts on a firm's earnings per share (Feps) in year t, scaled by the actual earnings per share (Meps). *FDISP* is measured by the standard deviation of Feps, scaled by earnings per share (Meps). The calculations are shown as below:

$$FREE_{i,t} = \frac{abs\left[Meps_{i,t} - Mean\left(Feps_{i,t}\right)\right]}{abs\left(Meps_{i,t}\right)} \tag{1}$$

$$FDISP_{i,t} = \frac{sd\left(Feps_{i,t}\right)}{abs\left(Meps_{i,t}\right)} \tag{2}$$

where each Feps for firm i in year t is the latest forecast value of a certain analyst before the release of the annual fiscal report of year t, so the Feps is made in year t or year t + 1. Considering that some forecast results are the outcome of a group work by several analysts, to facilitate the code running, we extract the analyst's name listed in the first place as the symbol to distinct different forecast results for each firm-year.

4.2.2. Independent variable

The independent variable is ESG rating disagreement (*Disagreement*). We define it as the coefficient of variation of ratings because CV is a dimensionless number. Following Christensen et al. (2022), we firstly compute the standard deviation of all rating scores that firm i has received from rating agencies for its performance in year t. Then, we standardize the standard deviation by the average rating score grouped by each firm-year observation. Thus, we obtain disagreements on ESG ratings of each company. See eq. (3) for details:

$$Disagreement = SD(Score)/Mean(Score) \tag{3}$$

among which, *SD (Score)* is the standard deviation and *Mean (Score)* is the average rating score of all ratings that a company has from each rating agency.

4.3. Regression model and control variables

To test the impact of ESG rating disagreement on the quality of analyst forecast, this study constructs the following model:

$$FERR(FDIS)_{i,t+1} = \beta_0 + \beta_1 Disagreement_{i,t} + \sum \beta_i Control_{i,t} + Year + Industry \tag{4}$$

where the $FERR_{i,t+1}$ and $FDIS_{i,t+1}$ are analysts' earnings forecast error and forecast divergence for firm i in year t + 1 since analysts' assessment and forecast occur after the report of corporate ESG ratings. Following Lys and Soo (1995), Muslu et al. (2019), $Control_{i,t}$ consists following characteristics: firm size (*Size*), asset-liability ratio (*Lev*), profitability (*ROA*), book-to-market ratio (*BM*), nature of property rights (*SOE*), equity balance (*Balance*), proportion of independent directors (*Indep*), two positions in one (*Dual*), age of the company (*Age*), "Big 4" (*Big4*), the percentage of shares held by institutional investors (*Inshr*), earnings volatility (*Epsv*), information disclosure opacity (*Opac*), the number of analysts following the firm (*Analyst*). Besides, *Year* and *Industry* present the year and industry fixed effects respectively. The specific definitions of each variable are listed in Appendix A.

Table 1 reports the descriptive statistics of the entire sample. The average and median of *Disagreement* are 0.466 and 0.470 respectively, which presents a relatively great divergence among ESG rating results.

5. Empirical results and discussion

5.1. Baseline results

Table 2 reports the estimates of the impact of ESG rating disagreement on the quality of analyst forecasts. Column (1) and column (2) report the regression results without *Control*, showing a significantly positive association between analyst forecast error (*FERR*) and analyst forecast dispersion (*FDIS*). Columns (3) and (4) report the regression results after adding a series of control variables. It can be found that ESG rating disagreement can significantly enhance *FERR* and *FDIS*. Specifically, when ESG rating disagreement increases by 1 unit, *FERR* increases by 0.675 units and *FDIS* increases by 0.536 units. These significantly positive coefficients of ESG rating disagreement indicate that ESG rating disagreement is more likely to transmit "noise" and interfere with analysts' judgment of listed companies, thus lowering the quality of analysts' prediction. The above results strongly support our H1b.

5.2. Robustness and endogeneity

5.2.1. Robustness checks

We conduct a range of tests to test the robustness of our results. First, considering that analyst characteristics are highly related to the earnings forecast quality, we control the following five variables related to analyst characteristics and run the baseline regression again: analyst working experience, analyst gender, analyst degree, number of forecast reports, and number of following companies. In Table 3 panel A, columns (1) and (2) report the regression results that show a significantly positive relationship between *Disagreement* and *FERR/FDIS*.

Second, we run the baseline regression with an extended sample. Our original sample starts in 2015, so the rating ranges could overlap as much as possible. Considering that the extended period is more conducive to verifying the impact of ESG rating disagreement on analyst forecast quality, we add data from 2012 to 2014 to construct a new sample. It begins in 2012 based on the requirement that each firm-year has at least two ratings. The regression results are showed in columns (3) and (4) of Table 3 panel A, the coefficients of ESG *Disagreement* on *FERR* and *FDIS* are significantly positive at the level of 5% and 1% respectively, which remain robust.

Third, Christensen et al. (2022) pointed out that firms can choose how much ESG information to disclose. Therefore, to mitigate the potential biases of self-selection or firm-level time-varying correlated omitted variables, we regress the model with firm fixed effect. Columns (5) and (6) of Table 3 panel A report that the results are still robust.

Forth, we follow Schiemann and Tietmeyer (2022) to include firm-clustered standard errors to account for the problem that residuals are very likely correlated across firms. Columns (7) and (8) of Table 3 panel A show the results after clustering firm, which stay robust.

Table 4
Endogeneity.

	Instrumental variable			PSM	
	First	Second			
	(1) Disagreement	(2) FERR	(3) FDIS	(4) FERR	(5) FDIS
Dis_mean	0.844***				
	(16.993)				
Disagreement		6.461***	2.013*	0.261*	0.322***
		(2.935)	(1.718)	(1.655)	(3.804)
SOE	−0.004	−0.200*	−0.054	−0.079	0.135
	(−1.227)	(−1.678)	(−0.846)	(−0.366)	(1.170)
Balance	−0.077***	0.063	−0.147	0.560	0.349
	(−7.488)	(0.150)	(−0.654)	(0.801)	(0.930)
InShr	0.003	−1.410***	−0.644***	−1.146***	−0.607***
	(0.461)	(−6.045)	(−5.184)	(−2.813)	(−2.779)
Dual	−0.005*	−0.137	−0.056	0.040	−0.021
	(−1.715)	(−1.305)	(−1.006)	(0.212)	(−0.209)
Indep	0.004	1.345	0.718*	3.187**	1.292
	(0.169)	(1.643)	(1.649)	(2.163)	(1.634)
Analyst	0.006***	−0.047	−0.024	−0.056	−0.020
	(3.367)	(−0.704)	(−0.677)	(−0.508)	(−0.334)
Big4	−0.065***	0.560**	0.220*	0.126	0.171
	(−13.925)	(2.480)	(1.827)	(0.397)	(1.005)
Opac	0.008***	0.258***	0.152***	0.406***	0.206***
	(3.844)	(3.256)	(3.596)	(2.950)	(2.783)
ROA	−0.713***	−12.062***	−7.781***	−19.236***	−10.229***
	(−28.355)	(−6.351)	(−7.695)	(−11.010)	(−10.914)
Lev	−0.061***	0.067	−0.239	−0.443	−0.183
	(−7.087)	(0.191)	(−1.273)	(−0.803)	(−0.617)
Size	0.027***	−0.285***	−0.045	−0.080	−0.023
	(14.688)	(−3.144)	(−0.925)	(−0.712)	(−0.387)
BM	−0.082***	0.145	−0.430**	−0.664	−0.815***
	(−10.987)	(0.441)	(−2.459)	(−1.482)	(−3.389)
Epsv	0.006*	0.651***	0.393***	0.531**	0.348***
	(1.702)	(4.685)	(5.319)	(2.266)	(2.766)
Age	0.004	0.134	−0.000	−0.222	−0.261
	(0.895)	(0.765)	(−0.005)	(−0.742)	(−1.630)
Constant	−0.433***	6.471***	3.195***	4.947**	2.855**
	(−9.729)	(4.313)	(4.000)	(2.098)	(2.256)
Industry FE	YES	YES	YES	NO	NO
Year FE	YES	YES	YES	NO	NO
N	11,081	11,081	11,081	3327	3327
Adjusted-R^2	0.432	0.047	0.071	0.073	0.071
Weak identification test					
Cragg-Donald Wald F statistic		5900.799			
Underidentification test					
Kleibergen-Paap rk LM statistic		1709.395			
p-value		0.000***			

Notes: This table provides results after controlling the endogeneity. Columns (1)–(3) report the results of instrumental variable estimation. The instrumental variable (*Dis_mean*) is calculated by the average of all firms' *Disagreement* in the same year grouped by industry. The coefficients of the first stage where *Dis_mean* is significantly associated with *Disagreement*, which meets with the requirement of correlation. The results of the second stage show that *Disagreement* has a significantly positive relationship with *FERR* and *FDIS*. The bottom of table shows statistics of weak identification test and underidentification test, indicating that the instrumental variable is valid. Columns (4) and (5) report the results of PSM. The coefficients are significant and positive, confirming the results in basic regression. Significance levels at $p <$ 10%, 5% and 1%, one-tailed, are indicated by *, ** and ***, respectively.

Table 5
Results of mechanism test.

	FERR		FDIS	
	(1)	(2)	(3)	(4)
	Low-quality accounting information	High-quality accounting information	Low-quality accounting information	High-quality accounting information
Disagreement	0.973*	−0.047	0.706***	0.278
	(1.940)	(−0.087)	(2.692)	(0.937)
SOE	−0.065	−0.474***	0.059	−0.298***
	(−0.403)	(−2.616)	(0.705)	(−2.995)
Balance	1.027*	−1.645***	0.420	−0.923***
	(1.864)	(−2.995)	(1.456)	(−3.063)
InShr	−1.363***	−1.313***	−0.501***	−0.689***
	(−3.774)	(−4.298)	(−2.651)	(−4.111)
Dual	−0.288*	−0.067	−0.150*	−0.001
	(−1.751)	(−0.495)	(−1.743)	(−0.018)
Indep	0.523	2.405**	0.177	1.213*
	(0.453)	(2.066)	(0.293)	(1.899)
Analyst	0.025	0.007	0.039	−0.039
	(0.268)	(0.074)	(0.794)	(−0.789)
Big4	0.178	0.187	0.084	0.059
	(0.877)	(0.479)	(0.794)	(0.274)
Opac	0.307***	0.294***	0.147**	0.189***
	(2.797)	(2.718)	(2.564)	(3.186)
ROA	−15.308***	−17.748***	−8.447***	−9.809***
	(−10.933)	(−12.614)	(−11.526)	(−12.706)
Lev	0.037	−0.681	−0.176	−0.494**
	(0.076)	(−1.545)	(−0.693)	(−2.041)
Size	−0.321***	−0.264**	−0.098*	−0.066
	(−3.259)	(−1.993)	(−1.904)	(−0.904)
BM	0.010	−0.460	−0.239	−0.874***
	(0.028)	(−1.043)	(−1.197)	(−3.616)
Epsv	0.887***	0.566***	0.419***	0.396***
	(4.199)	(3.069)	(3.789)	(3.918)
Age	−0.289	0.471**	−0.179	0.154
	(−1.116)	(1.974)	(−1.320)	(1.179)
Constant	11.960***	9.576***	5.793***	4.477***
	(5.273)	(3.453)	(4.879)	(2.942)
Industry FE	YES	YES	YES	YES
Year FE	YES	YES	YES	YES
N	5459	5460	5459	5460
Adjusted-R^2	0.077	0.077	0.074	0.092
p-value	0.002***		0.025**	

Notes: This table reports the results of mechanism test with information asymmetry. Coefficients of *Disagreement* in Columns (1)–(4) are significant and positive, and the *p*-value of inter-group coefficient difference test are also significant, which indicate that ESG rating disagreement has more negative impact on companies with low-quality information environment. The results support that ESG rating disagreement impairs analyst forecast quality by exacerbating information asymmetry. Significance levels at p < 10%, 5% and 1%, one-tailed, are indicated by *, ** and ***, respectively.

Fifth, we conduct two other methods to calculate ESG rating disagreement. Firstly, to build the industry-adjusted Disagreement (*Disagreement_Ind*). Specifically, we calculate an average rating value grouped by industry and year to scale the standard deviation of ratings in each firm-year observation, the same as that in the eq. (3). The specific processing method is shown in Eq. (5):

$$Disagreement\_Ind = sd[Score]/M(Score\_Ind) \tag{5}$$

Secondly, we follow Avramov et al. (2021) to construct a new independent variable of ESG rating disagreement (*Disagreement_avr*): We obtain 15 rater pairs from 5 rating providers. Since all rating scores have been re-scaled and now range from 0 to 100, we use the re-scaled scores to calculate differences and the standard deviation by two raters in each pair, and then compute the *Disagreement_avr* as the average pairwise standard deviation across all rater pairs in each firm-year observation.

Columns (1)–(4) of Table 3 panel B provide the regression results. We find that the associations between *FERR(FDIS)* and the industry-adjusted *Disagreement* are still significantly positive. *Disagreement_avr* impacts *FERR* and *FDIS* as what *Disagreement* does in our baseline regression, although the significant levels are lower. The results stay robust.

Sixth, we replace the measurement of dependent variables as follows. Following Dhaliwal et al. (2011), we scale the forecast errors by stock price (*P*) of firm i in the beginning of year t.

$$FERR\_D_{i,t} = \frac{abs\left[Meps_{i,t} - Mean\left(Feps_{i,t}\right)\right]}{P_{i,t}} \tag{6}$$

$$FDISP\_D_{i,t} = \frac{sd\left(Fesp_{i,t}\right)}{P_{i,t}} \tag{7}$$

Columns (6) and (7) of Table 3 panel B report that ESG rating disagreement is still strongly associated with *FERR* and *FDIS*, whose regression coefficients are 1.601 and 0.364 respectively. Thus we conclude that the measurement of *FERR* and *FDIS* does not impact our results.

5.2.2. Endogeneity

We adopt Instrumental Variable and Propensity Score Matching to control for the endogeneity. First, we use instrumental variable to mitigate the possibility of omitted variables. Based on the concept that the ESG performance of a certain company is affected by the performance of peers in the same industry, those peers' ESG performance is not directly related to analyst forecast quality of this company within the current period. Therefore, we follow Benlemlih and Bitar (2018) and construct the instrumental variable using the average of all firms' *Disagreement* in the same year grouped by industry (*Dis_mean*), and then conduct 2SLS regression. The results are reported in Table 4 columns (1)–(3). In the first stage, *Dis_avr* is positively correlated with the original independent variable *Disagreement* at a significant level, which meets the requirement of correlation. The Cragg-Donald Wald F statistic is 5900.799, which is greater than the critical value of 16.38 of the Stock-Yogo weak instrument test at the level of 10%, passing the weak instrumental variable test. The Kleibergen-Paap rk LM statistic is 1709.395, which is significant at the 1% level, indicating that there is no under-recognition. In the second stage, *Disagreement* has a significantly positive relationship with *FERR* and *FDIS*, which supports our results in the baseline regression.

We also conduct Propensity Score Matching to control the impact of other firm-level characteristics on analyst earning forecast. Since *Disagreement* is a continuous variable, we first sort *Disagreement* and divide it into three groups "low", "medium", and "high", and keep the "low" and "high" groups, which are assigned values of 0 and 1 respectively. Secondly, we apply 1:1 nearest neighbour matching to pair samples in "high" and "low" groups. Table 4 columns (4) and (5) report the regression results of PSM. The regression coefficients are 0.261 and 0.322 respectively, both significant at the 1% level. The above results indicate that our research conclusion is robust.

5.3. Mechanism test

In the preceding analysis, we found that ESG rating disagreement escalates analyst forecast error and dispersion. Based on our hypothesis development, we propose that ESG rating disagreement, embodying uncertainty, might impede analysts' capacity to effectively process corporate information, consequently escalating information processing costs and complicating analysis and forecasting tasks. We thus infer that information asymmetry likely serves as a channel between ESG rating disagreement and the quality of analyst forecasts. In this section, we investigate whether ESG rating disagreement aggravates information asymmetry and ultimately impairs analyst forecast quality.

The information environment of a firm significantly influences analyst forecasting. A robust information environment equips analysts with reliable data, enhancing forecast accuracy. Conversely, low-quality and low-transparent corporate information disclosure escalates information asymmetry, diminishing forecast quality.

Table 6
Gender diversity of board secretary, equity of nature and the effects of ESG rating disagreement.

	FERR		FDIS		FERR		FDIS	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Female board secretaries	Male board secretaries	Female board secretaries	Male board secretaries	State-owned enterprises	Non-state-owned enterprises	State-owned enterprises	Non-state-owned enterprises
Disagreement	−0.284	1.084***	0.255	0.635***	−0.822	1.253***	−0.220	0.789***
	(−0.420)	(2.597)	(0.717)	(2.808)	(−1.410)	(2.768)	(−0.701)	(3.247)
SOE	−0.108	−0.293**	−0.045	−0.080	.	.	.	.
	(−0.466)	(−2.096)	(−0.367)	(−1.055)	.	.	.	.
Balance	−1.587**	−0.113	−0.745*	−0.185	1.060*	−1.262**	0.406	−0.756***
	(−2.155)	(−0.247)	(−1.925)	(−0.749)	(1.682)	(−2.565)	(1.194)	(−2.864)
InShr	−2.383***	−0.863***	−1.022***	−0.429***	−1.748***	−1.414***	−0.618**	−0.692***
	(−5.444)	(−3.131)	(−4.440)	(−2.870)	(−3.189)	(−5.359)	(−2.091)	(−4.887)
Dual	−0.147	−0.205	−0.099	−0.063	−0.352	−0.142	−0.296**	−0.022
	(−0.777)	(−1.618)	(−0.992)	(−0.926)	(−1.443)	(−1.214)	(−2.254)	(−0.350)
Indep	1.125	1.471	0.759	0.659	0.447	1.988*	−0.103	1.234**
	(0.717)	(1.534)	(0.921)	(1.266)	(0.351)	(1.876)	(−0.150)	(2.172)
Analyst	−0.113	0.070	−0.082	0.017	0.112	−0.075	0.066	−0.052
	(−0.917)	(0.920)	(−1.269)	(0.410)	(1.085)	(−0.914)	(1.196)	(−1.177)
Big4	1.052***	−0.117	0.593***	−0.055	0.199	−0.054	0.104	0.056
	(2.967)	(−0.580)	(3.180)	(−0.505)	(0.867)	(−0.204)	(0.837)	(0.397)
Opac	0.289**	0.293***	0.166**	0.160***	−0.044	0.433***	0.042	0.212***
	(2.067)	(3.182)	(2.260)	(3.194)	(−0.332)	(4.585)	(0.597)	(4.177)
ROA	−17.925***	−16.238***	−8.197***	−9.648***	−18.305***	−15.545***	−11.687***	−8.022***
	(−10.225)	(−13.817)	(−8.895)	(−15.135)	(−9.939)	(−13.411)	(−11.763)	(−12.907)
Lev	−0.924	−0.147	−0.363	−0.373*	−0.628	−0.120	−0.460*	−0.330
	(−1.552)	(−0.385)	(−1.162)	(−1.795)	(−1.215)	(−0.291)	(−1.653)	(−1.487)
Size	−0.052	−0.162**	0.003	0.008	−0.283***	−0.072	−0.075	0.018
	(−0.398)	(−1.977)	(0.038)	(0.174)	(−2.717)	(−0.780)	(−1.333)	(0.367)
BM	−0.931*	−0.190	−0.734***	−0.580***	1.022**	−1.039***	0.118	−0.954***
	(−1.772)	(−0.569)	(−2.658)	(−3.210)	(2.376)	(−2.820)	(0.508)	(−4.828)
Epsv	0.519**	0.726***	0.353***	0.445***	0.287	0.741***	0.193	0.439***
	(2.055)	(4.364)	(2.658)	(4.924)	(1.062)	(4.557)	(1.324)	(5.029)
Age	0.387	0.225	−0.093	0.110	−0.223	0.256	−0.014	0.003
	(1.206)	(1.067)	(−0.552)	(0.967)	(−0.724)	(1.198)	(−0.084)	(0.028)
Constant	9.610***	5.924***	6.101***	2.249**	10.849***	5.862***	4.747***	3.053***
	(3.333)	(3.324)	(4.025)	(2.326)	(4.522)	(3.006)	(3.668)	(2.919)
Industry FE	YES	YES	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES	YES	YES
N	3422	7334	3422	7334	3958	7123	3958	7123
Adjusted-R^2	0.096	0.065	0.097	0.077	0.057	0.082	0.072	0.087
p-value	0.000***		0.007***		0.000***		0.000***	

Notes: This table describes results of heterogeneity test of the gender of board secretaries and equity nature of corporate respectively in columns (1)–(4) and columns (5)–(8). Firstly, the sample is divided by the gender of board secretaries. Columns (2) and (4) report the significantly positive relation between *Disagreement* and *FERR* and *FDIS* in companies with male board secretaries, while in columns (1) and (3) there is no such pronounced relation in the group of "Female board secretaries". The results indicate that ESG rating disagreement impacts analysts forecasting more in companies with worse information disclosure. Secondly, the sample is divided into groups of SOE and non-SOE. Columns (6) and (8) report the significantly positive relation between *Disagreement* and *FERR/FDIS* in non-SOE, while columns (5) and (7) do not show any significant association in the group of SOE. The results reveal that analyst forecast is under more interference in non-SOE whose ESG information disclosure is less adequate and standardized than SOE. Significance levels at $p < 10\%$, 5% and 1%, one-tailed, are indicated by *, ** and ***, respectively.

Therefore, following Liu et al. (2023), we utilize earnings management as a proxy for the transparency of firm-level information disclosure. Specifically, we adopt Hutton, Marcus, and Tehranian (2009) approach of using "the average value of manipulative accruals (*Acc*) of firms over the past three years" as a measure of earnings management. The sample is divided into two groups based on the median of *Acc*. Companies with manipulative accruals above the median are categorized as having "low-quality accounting information", and those below as having "high-quality accounting information".

Table 5 reports the regression results. We find significant relations between ESG rating disagreement and *FERR (FDIS)* at the level of 10% and 1% respectively, in columns (1) and (3), that is the group of "low-quality accounting information ", while we do not observe such associations in the group of "high-quality accounting information" in columns (2) and (4). The coefficient difference between the two groups has been tested 1000 times by Fisher's Permutation test and its empirical *P*-value is significant at the level of 1% and 5% respectively.

These results show that when analysts conduct earnings forecasts of companies with poorer information environments, the forecast error and dispersion will increase with the impact of ESG rating disagreement, since it may cause more uncertainty and costs of information processing. The above finding can, to some degree, support our deduction that ESG rating disagreement will exacerbate information asymmetry and then impair analyst forecast quality.

5.4. Heterogeneity tests

5.4.1. Information environment

As verified in the mechanism test, ESG rating disagreement of companies with poor-quality accounting information will further impair analyst forecast quality by increasing information asymmetry. As corporate information disclosure is highly associated with information environment, it is possible that analyst will be interfered more when encountering ESG rating disagreement in a worse information environment. Therefore, we conduct a series of heterogeneity tests based on the information environment.

(1) Gender diversity of board secretary

The role board secretaries is a unique institution in China's corporate management. This senior executive role is responsible for information disclosure and organizations' relationships with their investors (Xing,

Table 7
Compliance with GRI, third-party authentication and the effects of ESG rating disagreement.

	FERR		FDIS		FERR		FDIS	
	Non-compliance with GRI	Compliance with GRI	Non-compliance with GRI	Compliance with GRI	Non-authenticated CSR reports	Authenticated CSR reports	Non-authenticated CSR reports	Authenticated CSR reports
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Disagreement	0.636*	0.972	0.521**	0.773	0.673*	−6.720	0.537***	−5.526*
	(1.653)	(0.868)	(2.525)	(1.260)	(1.912)	(−1.557)	(2.843)	(−1.744)
SOE	−0.160	−0.864**	−0.022	−0.430**	−0.234**	−0.569	−0.061	−0.469
	(−1.265)	(−2.567)	(−0.322)	(−2.333)	(−1.969)	(−0.479)	(−0.952)	(−0.538)
Balance	−0.335	−1.524	−0.235	−0.876	−0.416	2.509	−0.271	1.372
	(−0.807)	(−1.531)	(−1.054)	(−1.606)	(−1.077)	(0.781)	(−1.309)	(0.581)
InShr	−1.480***	−0.571	−0.679***	−0.190	−1.384***	1.381	−0.640***	1.031
	(−6.029)	(−0.784)	(−5.159)	(−0.476)	(−5.965)	(0.414)	(−5.139)	(0.422)
Dual	−0.147	−0.370	−0.043	−0.291*	−0.166	0.901	−0.062	0.447
	(−1.335)	(−1.173)	(−0.725)	(−1.683)	(−1.586)	(0.894)	(−1.100)	(0.604)
Indep	1.123	4.627**	0.468	3.319***	1.399*	6.695	0.715	5.472
	(1.264)	(2.260)	(0.982)	(2.958)	(1.709)	(0.929)	(1.628)	(1.034)
Analyst	0.017	−0.146	−0.008	−0.043	−0.011	1.466*	−0.016	1.009
	(0.248)	(−0.758)	(−0.208)	(−0.404)	(−0.166)	(1.750)	(−0.461)	(1.641)
Big4	0.170	0.140	0.111	0.074	0.224	−1.270	0.144	−1.048
	(0.798)	(0.462)	(0.977)	(0.445)	(1.260)	(−1.027)	(1.508)	(−1.154)
Opac	0.342***	0.013	0.183***	−0.028	0.307***	0.513	0.162***	0.393
	(4.209)	(0.062)	(4.198)	(−0.241)	(4.016)	(0.610)	(3.953)	(0.637)
ROA	−16.570***	−13.762***	−9.090***	−6.158***	−16.507***	−3.260	−8.955***	0.963
	(−15.977)	(−4.803)	(−16.342)	(−3.922)	(−16.997)	(−0.314)	(−17.177)	(0.127)
Lev	−0.194	−1.222	−0.303*	−0.481	−0.313	0.819	−0.343**	1.391
	(−0.573)	(−1.181)	(−1.667)	(−0.848)	(−0.975)	(0.226)	(−1.991)	(0.523)
Size	−0.127	−0.010	−0.004	−0.041	−0.120*	−1.110	−0.001	−0.706
	(−1.611)	(−0.062)	(−0.090)	(−0.447)	(−1.749)	(−1.645)	(−0.027)	(−1.425)
BM	−0.530*	1.277*	−0.681***	0.700*	−0.331	4.125	−0.555***	2.677
	(−1.735)	(1.712)	(−4.153)	(1.713)	(−1.183)	(1.370)	(−3.693)	(1.211)
Epsv	0.717***	0.458	0.416***	0.371*	0.676***	−0.533	0.402***	−0.517
	(4.857)	(1.172)	(5.255)	(1.732)	(4.876)	(−0.440)	(5.411)	(−0.580)
Age	0.204	−0.162	0.012	−0.000	0.161	−0.255	0.009	0.158
	(1.084)	(−0.333)	(0.115)	(−0.002)	(0.921)	(−0.152)	(0.097)	(0.128)
Constant	6.827***	3.992	3.349***	3.338	6.717***	20.951	3.232***	11.968
	(4.075)	(0.947)	(3.727)	(1.446)	(4.504)	(1.506)	(4.037)	(1.172)
Industry FE	YES	YES	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES	YES	YES
N	9829	1240	9829	1240	10,971	98	10,971	98
Adjusted-R^2	0.070	0.080	0.079	0.077	0.070	0.220	0.077	0.219
p-value	0.002***		0.000***		0.000***		0.000***	

Notes: This table describes results of heterogeneity test based on whether the CSR reports comply with the GRI and have a third-party authentication. In columns (1)–(4), the sample is divided into groups based on compliance with GRI standards. Columns (1) and (3) report the significantly positive relation between *Disagreement* and *FERR* and *FDIS* in companies do not comply with GRI standards, while columns (2) and (4) do not show such association in the group of "compliance with GRI". The results show that ESG rating disagreement has more impacts on analysts forecasting in companies with less CSR disclosure. In columns (5)–(8), the sample is divided into two groups according to whether CSR reports have undergone tje third-party authentication. Columns (5) and (7) report the significantly positive relation between *Disagreement* and *FERR* and *FDIS*, while columns (6) and (8) show a significant and negative one. The results show that credible CSR reports provide more useful information to analysts, thus could mitigate the interference of *Disagreement*. Significance levels at $p < 10\%$, 5% and 1%, one-tailed, are indicated by *, ** and ***, respectively.

Duan, & Hou, 2019). Studies have confirmed that board secretaries' personal characteristics exert significant influence on information asymmetry and earnings forecast quality (Kwak, Ro, & Suk, 2012; Xing et al., 2019). According to researches on gender diversity of boards, female participation positively affects the ESG performance and ESG information disclosure (Alkhawaja, Hu, Johl, & Nadarajah, 2023; Velte, 2016), because women are more concerned about social challenges and stakeholders' needs (Harjoto, Laksmana, & Lee, 2015). Therefore, it is reasonable to expect that female board secretaries, as the important board member, will improve firms' information environment and promote the quality of ESG information disclosure. As a result, financial analysts could gain more efficient information when facing ESG rating disagreement and reduce the impairment of forecast quality.

To test this assumption, we build two sub-samples based on the gender of board secretaries. The regression results are listed in Table 6 columns (1)–(4). As shown, the positive relation between ESG rating disagreement and *FERR/FDIS* is only significant in the "male board secretaries" group, which indicates that firms with female board secretaries have better ESG information and alleviate the disturbance of ESG rating disagreement to analyst forecast quality.

(2) The equity nature of corporate

The state-owned enterprises play the leading role in the spread and promotion of ESG practice in China. The State-Owned Assets Supervision and Administration Commission (SASAC) issued the *Work Plan for Improving the Quality of Listed Companies Controlled by Central Enterprises,* which requires the establishment of a sound ESG system. In contrast, for non-state-owned listed companies, there are no mandatory regulations concerning ESG reports yet. Most listed enterprises could choose whether to disclose and how much to disclose ESG information. Therefore, compared to non-state-owned enterprises, SOE may provide a greater amount of ESG information in a more standardized and more comparable format. In this case, analysts will face less information processing costs when forecasting SOE's earnings performance. We speculate that the disturbance of ESG rating disagreement to analyst forecast quality could be less in SOE than in non-SOE.

We divide the sample into two groups based on their equity nature. The regression results are shown in Table 6 columns (5)–(8). As reported in columns (6) and (8), when analyzing non-state-owned enterprises,

Table 8
Connection with HKSE and the effects of ESG rating disagreement.

	FERR		FDIS	
	Eligible stocks	Ineligible stocks	Eligible stocks	Ineligible stocks
	(1)	(2)	(3)	(4)
Disagreement	0.200	0.761**	−0.123	0.645***
	(0.198)	(2.013)	(−0.226)	(3.178)
SOE	0.114	−0.242*	0.004	−0.067
	(0.287)	(−1.945)	(0.021)	(−1.006)
Balance	−2.118**	−0.177	−1.267**	−0.177
	(−1.965)	(−0.421)	(−2.171)	(−0.785)
InShr	−1.925***	−1.375***	−1.125***	−0.611***
	(−3.182)	(−5.516)	(−3.434)	(−4.565)
Dual	−0.194	−0.173	−0.050	−0.078
	(−0.699)	(−1.553)	(−0.332)	(−1.301)
Indep	3.591*	1.136	2.340**	0.537
	(1.695)	(1.295)	(2.040)	(1.141)
Analyst	0.315*	−0.050	0.066	−0.027
	(1.740)	(−0.727)	(0.677)	(−0.736)
Big4	−0.322	0.315	−0.087	0.169
	(−0.862)	(1.534)	(−0.427)	(1.532)
Opac	0.440*	0.309***	0.140	0.170***
	(1.834)	(3.843)	(1.082)	(3.949)
ROA	−17.704***	−16.178***	−9.003***	−8.896***
	(−6.290)	(−15.616)	(−5.906)	(−15.996)
Lev	0.417	−0.404	−0.209	−0.384**
	(0.415)	(−1.192)	(−0.384)	(−2.106)
Size	−0.172	−0.104	0.014	0.006
	(−0.873)	(−1.410)	(0.133)	(0.157)
BM	0.028	−0.337	−0.163	−0.573***
	(0.034)	(−1.138)	(−0.363)	(−3.607)
Epsv	0.853***	0.656***	0.576***	0.379***
	(2.589)	(4.374)	(3.226)	(4.706)
Age	1.180***	0.075	0.497**	−0.022
	(2.607)	(0.396)	(2.027)	(−0.219)
Constant	0.377	6.847***	−0.954	3.266***
	(0.087)	(4.272)	(−0.405)	(3.796)
Industry FE	YES	YES	YES	YES
Year FE	YES	YES	YES	YES
N	1145	9941	1145	9941
Adjusted-R^2	0.131	0.068	0.115	0.077
p-value	0.000***		0.000***	

Notes: This table describes the results of heterogeneity test, where the sample is divided into two groups according to whether the securities are connected with HKSE. Columns (2) and (4) report the significantly positive relation between *Disagreement* and *FERR* and *FDIS*, while columns (1) and (3) do not. The results show that illegible stocks are less standardized in ESG information disclosure and thus could not provide valuable information for analysts as much as eligible stocks do. Ultimately, analyst forecast will be impaired in companies who are not illegible stocks. Significance levels at $p < 10\%$, 5% and 1%, one-tailed, are indicated by *, ** and ***, respectively.

analyst forecast error and forecast dispersion are both significantly related to the increase of *Disagreement*. However, this positive relation is not observed in the group of state-owned enterprises. The results verify our speculation that SOE with higher-quality ESG disclosure could reduce the negative influence of ESG rating disagreement on analyst forecast.

(3) Compliance with GRI

The Global Reporting Initiative (GRI) provides a framework for companies' information disclosure on sustainable development, which improves the overall information quality and the usefulness of the text to help analysts interpret the report (Kimbrough et al., 2024). Therefore, if companies comply with the GRI framework in their Corporation Social Responsibility reports, the disclosure quality will be elevated. We hypothesize that high-quality CSR disclosures can help analysts navigate the uncertainty stemming from ESG rating disagreements, thereby reducing their forecast errors and dispersion. For this test, the sample is divided into groups based on compliance with GRI standards. Table 7 columns (1)–(4) report the results. In the "non-compliance with GRI" group, a significantly positive correlation is observed, while columns (2) and (4) of "compliance with GRI" do not reflect such a positive relation. We perceive that firms that comply with the GRI disclosure framework have a better information environment, which can mitigate the negative impact caused by ESG rating disagreement. The *p*-value of Fisher's Permutation test is at the significant level of 1% for both *FERR* and *FDIS*.

(4) Third-party authentication

Third-party authentication institutions, being independent of listed companies, are perceived as objective and credible. Previous study pointed out that unaudited CSR reports lack credibility, and are often deemed less credible and useful by financial analysts, interfering the information integration into analysts' earning forecasts (Shi et al., 2023). Therefore, we deduce that a third-party audit improves the credibility and quality of enterprises' CSR disclosure, and provides more utilizable information for analyst earnings forecast. To test this, companies are categorized into two groups according to whether their CSR reports have undergone third-party authentication. As shown in columns (5)–(8) of Table 7, the "noise effect" of ESG rating disagreement on analyst forecast error and dispersion is more pronounced in companies whose CSR reports are not verified by any third party, while the coefficients of *Disagreement* in the "authenticated CSR reports" group are even negative. The p-value of Fisher's Permutation test is significant at the level of 1%.

The above results illustrate that a high-quality CSR disclosure indeed relieves the negative impact of ESG rating disagreement on analyst earnings forecast by improving the reliability and richness of information sets that analysts could access.

(5) Connection with the Hong Kong Stock Exchange

With the development of market liberalization and the implementation of a series of financial reforms, the Mainland stock market has been more correlated with the Hong Kong stock market. For instance, there are stocks of both A-share listing and H-share listing. Also, the launch of Shanghai-Hong Kong Stock Connect (SHSC) and Shenzhen-Hong Kong Stock Connect (SZSC) established mutual market access to securities trading and clearing between the Mainland and Hong Kong.

As an open and mature market with diversified investors from all over the world, the Hong Kong Stock Market (HKSE) has been engaged in the practice of ESG disclosure for years. In 2013, the HKSE first introduced the *ESG Reporting Guide* to provide the listed companies with a clear framework for ESG disclosure. To improve the regulation of ESG disclosure and address investors' demands, the HKSE issued more requirements in 2019 and 2021.

Considering the deep linkage between the Mainland stock market and the Hong Kong stock market, there may be a spillover of the ESG disclosure regulation to AH stocks and eligible stocks connected with HKSE. On the one hand, after the launch of SHSC and SZSC, foreign investors (mainly institutional investors) have entered the Mainland stock market. As professional securities traders from mature markets, they may require more standardized ESG information disclosure of corporate. On the other hand, stocks listed simultaneously on the A-share market and H-share market are under stricter disclosure regulations required by the updated *ESG Reporting Guide*. Therefore, AH stocks and eligible stocks of Shanghai/Shenzhen-Hong Kong Connect tend to outperform other A-share listed companies in ESG information disclosure. In this case, we assume that financial analysts could extract more valuable information when forecasting the earning performance of companies connected with the Hong Kong stock market, and then they could relieve the disturbance of ESG rating disagreement to forecast quality.

To examine our assumption, we divide the entire sample into "Eligible stocks" group and "Ineligible stocks" group. As shown in Table 8 columns (2) and (4), *Disagreement* significantly enhances forecast error and forecast dispersion in the group of "Ineligible stocks". There is no pronounced association in the group of "Eligible stocks". The results reveal that listed companies not included in the SHSC/SZSC do puzzle analysts' earning forecast more than those eligible stocks, which supports that eligible stocks could provide ESG information of higher

Table 9
Work experience, degree of diligence and the effects of ESG rating disagreement.

	FERR		FDIS		FERR		FDIS	
	More Experienced	Less Experienced	More Experienced	Less Experienced	More diligent	Less diligent	More diligent	Less diligent
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Disagreement	0.038	1.240***	0.068	0.960***	0.128	1.095**	0.156	0.848***
	(0.074)	(2.597)	(0.246)	(3.688)	(0.255)	(2.213)	(0.583)	(3.179)
SOE	−0.192	−0.266	−0.049	−0.080	−0.204	−0.263	−0.063	−0.070
	(−1.109)	(−1.631)	(−0.529)	(−0.903)	(−1.221)	(−1.549)	(−0.698)	(−0.765)
Balance	−0.831	0.129	−0.504*	0.005	−1.412***	0.686	−0.648**	0.145
	(−1.481)	(0.243)	(−1.695)	(0.017)	(−2.606)	(1.253)	(−2.229)	(0.490)
InShr	−1.341***	−1.411***	−0.611***	−0.661***	−1.443***	−1.270***	−0.666***	−0.584***
	(−4.012)	(−4.370)	(−3.447)	(−3.753)	(−4.454)	(−3.808)	(−3.835)	(−3.250)
Dual	−0.012	−0.354**	0.017	−0.160**	−0.106	−0.232	−0.074	−0.058
	(−0.076)	(−2.442)	(0.212)	(−2.022)	(−0.724)	(−1.554)	(−0.944)	(−0.725)
Indep	1.225	1.637	0.786	0.704	1.521	1.258	1.043*	0.401
	(1.022)	(1.471)	(1.237)	(1.160)	(1.317)	(1.087)	(1.684)	(0.642)
Analyst	0.008	−0.062	−0.003	−0.039	−0.049	−0.019	−0.045	−0.004
	(0.087)	(−0.693)	(−0.062)	(−0.811)	(−0.539)	(−0.208)	(−0.916)	(−0.076)
Big4	−0.019	0.347	0.008	0.221*	0.098	0.190	0.089	0.122
	(−0.074)	(1.431)	(0.057)	(1.670)	(0.402)	(0.756)	(0.686)	(0.900)
Opac	0.361***	0.249**	0.151**	0.173***	0.336***	0.261**	0.153***	0.158***
	(3.210)	(2.394)	(2.522)	(3.046)	(3.089)	(2.420)	(2.635)	(2.723)
ROA	−16.591***	−16.455***	−8.597***	−9.419***	−13.969***	−19.048***	−7.765***	−10.260***
	(−11.957)	(−12.038)	(−11.683)	(−12.636)	(−10.303)	(−13.618)	(−10.681)	(−13.610)
Lev	−0.934**	0.307	−0.757***	0.068	−0.563	−0.072	−0.548**	−0.176
	(−1.995)	(0.694)	(−3.047)	(0.280)	(−1.245)	(−0.159)	(−2.260)	(−0.714)
Size	−0.032	−0.186**	0.043	−0.024	−0.055	−0.175*	0.033	−0.026
	(−0.321)	(−1.996)	(0.810)	(−0.479)	(−0.563)	(−1.818)	(0.632)	(−0.496)
BM	−0.343	−0.376	−0.405*	−0.771***	−0.336	−0.286	−0.591***	−0.524**
	(−0.853)	(−0.962)	(−1.899)	(−3.615)	(−0.860)	(−0.710)	(−2.822)	(−2.414)
Epsv	0.505**	0.786***	0.335***	0.450***	0.435**	0.884***	0.286***	0.512***
	(2.482)	(4.187)	(3.105)	(4.399)	(2.247)	(4.467)	(2.753)	(4.798)
Age	0.311	−0.063	0.073	−0.079	0.098	0.136	0.011	−0.020
	(1.189)	(−0.269)	(0.526)	(−0.617)	(0.394)	(0.554)	(0.083)	(−0.149)
Constant	5.059**	8.208***	2.457**	3.651***	5.583**	7.903***	2.593**	3.761***
	(2.306)	(4.027)	(2.111)	(3.285)	(2.572)	(3.805)	(2.228)	(3.360)
Industry FE	YES	YES	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES	YES	YES
N	5495	5477	5495	5477	5486	5486	5486	5486
Adjusted-R^2	0.072	0.077	0.069	0.093	0.062	0.088	0.068	0.094
p-value	0.002***		0.000***		0.004***		0.322	

Notes: This table reports the results of heterogeneity test of analysts' work experience and degree of diligence. In columns (1)–(4), the sample is divided into two groups according to analysts' work experience, which is measured by "the number of quarters since the analyst made the first earnings forecast until the end of the sample year". Columns (2) and (4) report the significantly positive relation between *Disagreement* and *FERR* and *FDIS in the group of "less experienced"*, while columns (1) and (3) do not report such a relation in the group of "more experienced". The results supports our deduction that less experienced analysts are more susceptible to the 'noise effect' of ESG rating disagreement. In columns (5)–(8), the sample is divided into two groups according to analysts' diligence degree, which is measured by "number of research reports". Columns (6) and (8) report the significantly positive relation between *Disagreement* and *FERR* and *FDIS in the group of "less diligent"*, while columns (5) and (7) do not report such a relation in the group of "more diligent". The results supports that less diligent analysts are interfered more by ESG rating disagreement. Significance levels at $p < 10\%$, 5% and 1%, one-tailed, are indicated by *, ** and ***, respectively.

quality for financial analysts and help to lessen the "noise" of ESG rating disagreement.

5.4.2. Analyst capabilities

Furthermore, prior studies have also identified analysts' capabilities as another key determinant of forecast quality (Dang et al., 2021). If analysts have strong professional ability and rich information channels, they may acquire more and better information sets and could outperform peers at information processing. Thus, they are expected to give higher-quality earnings predictions than other analysts who do not have such traits. Based on the preceding results, ESG rating disagreement may increase analyst forecast error and forecast dispersion by increasing information uncertainty and information redundancy. We, therefore, assume that analysts who are more skilled at information processing can perform better in dealing with ESG rating disagreement. To explore such relation, we measure analyst ability by work experience, degree of diligence and whether a star analyst.

(1) Work experience

Experienced analysts usually gain superior information access than less experienced ones, and have accumulated extensive professional knowledge and interpretative skills (Clement, 1999), which bolster their information processing capabilities, reduce information asymmetry and improve earnings prediction accuracy (Hilary & Shen, 2013). Therefore, this paper measures analysts' work experience by "the number of quarters since the analyst made the first earnings forecast until the end of the sample year" (*Quarters*), that is the total working time of a certain analyst. Considering that each firm-year observation corresponds to more than one analyst, we use the average value of all analysts' working time (*Quarters*) within each firm-year group as the proxy for working experience. The sample is split into two sub-samples of "more experienced" and "less experienced" by the median of *Quarters*. Regression results in Table 9 columns (1)–(4) show that *Disagreement* has a significantly positive correlation with *FERR* and *FDIS* in the group of "less experienced", but not in the group "more experienced", confirming that less experienced analysts are more susceptible to the 'noise effect' of ESG rating disagreement. The *p*-value of permutation test is still statistically significant.

(2) Degree of diligence

The quality of an analyst's earnings forecast is associated with their diligence. More diligent analysts are more skilled in interpreting information, thereby reducing prediction errors. In this case, we use the "number of research reports" as the indicator of analyst diligence. Since

Table 10
Star analyst and the effects of ESG rating disagreement.

	FERR		FDIS	
	Star analyst	Non-star analyst	Star analyst	Non-star analyst
	(1)	(2)	(3)	(4)
Disagreement	−0.013	0.878**	0.007	0.669***
	(−0.018)	(2.231)	(0.016)	(3.178)
SOE	−0.572**	−0.137	−0.127	−0.040
	(−2.180)	(−1.035)	(−0.878)	(−0.563)
Balance	−0.433	−0.455	−0.515	−0.226
	(−0.529)	(−1.052)	(−1.141)	(−0.979)
InShr	−1.667***	−1.289***	−0.779***	−0.601***
	(−3.134)	(−5.023)	(−2.659)	(−4.381)
Dual	−0.418*	−0.106	−0.312**	−0.008
	(−1.761)	(−0.921)	(−2.381)	(−0.131)
Indep	1.617	1.244	0.088	0.834*
	(0.904)	(1.369)	(0.089)	(1.716)
Analyst	0.004	−0.017	−0.029	−0.012
	(0.026)	(−0.239)	(−0.367)	(−0.302)
Big4	−0.105	0.191	−0.144	0.153
	(−0.259)	(0.990)	(−0.642)	(1.488)
Opac	−0.203	0.431***	−0.053	0.213***
	(−1.234)	(5.034)	(−0.584)	(4.654)
ROA	−22.028***	−14.852***	−11.412***	−8.213***
	(−10.238)	(−13.749)	(−9.630)	(−14.214)
Lev	−2.263***	0.220	−1.494***	−0.059
	(−3.224)	(0.616)	(−3.863)	(−0.309)
Size	−0.128	−0.120	0.079	−0.018
	(−0.833)	(−1.580)	(0.934)	(−0.438)
BM	−0.810	−0.180	−1.065***	−0.439***
	(−1.266)	(−0.580)	(−3.022)	(−2.640)
Epsv	0.605*	0.698***	0.426**	0.397***
	(1.843)	(4.590)	(2.357)	(4.884)
Age	0.796**	−0.005	0.205	−0.042
	(2.138)	(−0.024)	(0.999)	(−0.405)
Constant	8.504**	6.634***	3.464*	3.322***
	(2.424)	(4.025)	(1.793)	(3.767)
Industry FE	YES	YES	YES	YES
Year FE	YES	YES	YES	YES
N	2153	8928	2153	8928
Adjusted-R^2	0.093	0.071	0.095	0.077
p-value	0.000***		0.000***	

Notes: This table reports results of heterogeneity test, where the sample is divided into two groups according to whether the analyst is a star analyst. Columns (2) and (4) report the significantly positive relation between *Disagreement* and *FERR* and *FDIS in the group of "non-star analysts"*, while columns (1) and (3) show a negative relation in the group of "more diligent", though not significant. The results indicates that non-star analysts are more vulnerable to the "noise" of ESG rating disagreements, whereas star analysts can effectively counteract such impact. Significance levels at p < 10%, 5% and 1%, one-tailed, are indicated by *, ** and ***, respectively.

each firm is followed by several analysts in one year, we group analysts by firm-year and sum their number of research reports. Then we scale the total by the number of analysts in each firm-year group to obtain a unique number of reports (*Diligence*) as the basis for grouping. The sample is divided into "more diligent" and "less diligent" groups according to the median of *Diligence*. Results in Table 9 columns (5)–(8) reveal that ESG rating disagreement significantly correlates with increased forecast error and dispersion only in the "less diligent" group. The results prove that diligent analysts, through extensive information collection, can alleviate the negative impact of ESG rating disagreements on forecast quality.

(3) Star analyst

Contrasting with non-star analysts, who predominantly rely on publicly disclosed financial reports for predictions, star analysts, known for their superior professional capabilities, access a broader range of firm-level private information, leading to more accurate forecasts (Fang & Yasuda, 2009). Additionally, driven by factors such as reputation and compensation, star analysts are more inclined to gather extensive private information to enhance forecast quality (Meng, 2015). Based on this analysis, star analysts, equipped with professional competence and rich information resources, are possibly more adept at mitigating the disruptions caused by ESG rating disagreements. Consequently, they can produce higher-quality forecasts compared to their non-star peers. Therefore, we construct sub-samples by whether there is a star analyst within each firm-year observation. To address the problem that the firm-year observation does not uniquely identify the data of analyst, we take the following measures to construct a proxy index for "star analyst", so that there is a one-to-one correspondence. Firstly, we regard each firm-year as a group, and assign groups with at least one star analyst as 1, while those with no star analyst as 0. Next, we divide the entire sample into two sub-samples based on the dummy. Observations corresponding to index 0 are grouped as "non-star analyst", and the others as "star analyst" group. The regression results, as presented in Table 10, indicate a significantly positive correlation of *Disagreement* with forecast errors and dispersion among non-star analysts. Conversely, in the "star analyst" group, *Disagreement* exhibits a negative correlation with *FERR* and *FDIS*. This suggests that non-star analysts are more vulnerable to the "noise" of ESG rating disagreements, whereas star analysts can effectively counteract such impact.

6. Conclusion

In this study, we examine the impact of ESG rating disagreement on analysts' forecast error and forecast dispersion. While existing researches primarily focus on reasons behind ESG rating disagreements (Christensen et al., 2022; Kimbrough et al., 2024), our investigation sheds light on the market consequences of such disagreements from the perspective of analysts, who are crucial market participants providing value-related firm information.

Using samples consisting of ESG ratings of Chinese A-share listed companies from 2015 to 2021 by six rating agencies including RSK, SynTao Green Finance, Hexun, Bloomberg, Huazheng and Wind, we find a significant increase in analyst forecast error and dispersion due to ESG rating disagreement. The mechanism test verifies that this association originates from increased firm-level information asymmetry with greater ESG rating disagreement. Further analysis reveals that this trend is more pronounced in firms with male board secretaries, non-standardized and unverified CSR reports, and firms not state-owned, not connected with HKSE. However, analysts who are star analysts, with extensive work experience and high diligence, can mitigate the negative effect of ESG rating divergence on forecast quality.

This study responds to the calls for further explorations of the consequences of ESG rating disagreement (Christensen et al., 2022) by contributing new insights into analyst forecast accuracy within the Chinese stock market. Also, our results hold practical significance for improving ESG practices and promoting the establishment of ESG evaluation standards in China. In addition, we propose recommendations for three key participants in the capital market: First of all, the government should strive to improve the ESG disclosure standards, developing a domestic ESG system aligned with China's context and international market developments, thereby enhancing the comparability of ESG ratings and their positive role as investment references while minimizing negative impacts. Secondly, listed companies should actively implement green development and fulfil social responsibilities, focusing on higher-quality and more transparent ESG disclosure to reduce the adverse effects of ESG rating disagreement. Lastly, analysts are encouraged to enhance their professional abilities and expand their information channels, as a standardized ESG evaluation system is yet to be established. By doing so, they can lessen the disruption of ESG rating disagreement on their earnings forecasts, thereby providing more valuable market insights and effectively fulfilling their role as information intermediaries in the capital market.

Declaration of competing interest

We declare that we have no financial and personal relationships with other people or organizations that can inappropriately influence our work, there is no professional or other personal interest of any nature or kind in any product, service and/or company that could be construed as influencing the position presented in, or the review of, the manuscript entitled.

Data availability

Data will be made available on request.

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Appendix A. Variable Definitions

This table provides definitions of all variables using in this paper, including variable name, definition, and calculation. we use the coefficient of variation of ratings as the independent variable *Disagreement*, and follow Shi et al. (2023) to calculate the dependent variable *FERR* and *FDIS*. Besides, we add 14 control variables as follows.

Name	Variable	Definition
Analysts forecast error	*FERR*	The average of the absolute errors of all forecasts of earnings, scaled by the real EPS.
Analysts forecast disagreement	*FDIS*	The standard deviation of all forecasts of earnings made before the fiscal report released.
ESG rating disagreement	*Disagreement*	The standard deviation of all ESG ratings that a firm received, scaled by the average of ESG ratings of the firm.
Firm size	*Size*	The natural logarithm of the total assets at the end of year t.
Asset-liability ratio	*Lev*	Average total liabilities divided by average total assets.
Profitability	*ROA*	Return of Assets
Book-to-market ratio	*BM*	Book value divided by market value
Nature of property rights	*SOE*	If the firm is state-owned, the indicator variable equals 1 and 0 otherwise.
Equity balance	*Balance*	The percentage of shares held by the top2 to top10 shareholders.
Proportion of independent directors	*Indep*	The ratio of the number of independent directors to the number of all directors.
Two positions in one	*Dual*	If the two positions of chairman and the general manager are in one person, the indicator variable equals 1 and 0 otherwise.
Age of the company	*Age*	The natural logarithm of the year since the firm established, measured as ln(current fiscal year-starting year+1)
Big 4	*Big4*	If the firm is audited by the Big 4 accounting firms, the indicator variable equals 1 and 0 otherwise.
Percentage of shares held by institutional investors	*Inshr*	The percentage of shares held by institutional investors.
Earnings volatility	*Epsv*	The standard deviation of the previous three-year stock returns with dividend reinvested
Information disclosure opacity	*Opac*	An information transparency index based on the rating of information disclosure quality by Shenzhen Stock Exchange and Shanghai Stock Exchange. Excellent equals 0, Good equals 1, qualified equals 2, disqualified equals 3.
Number of analysts following	*Analyst*	The natural logarithm of the number of analysts following the firm through the year, calculated as ln(analysts number + 1).

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