European Financial Management

EUROPEAN FINANCIAL MANAGEMENT

ORIGINAL ARTICLE OPEN ACCESS

ESG Ratings Disagreement and Trading Behaviour

Mohammed Quotb[1,2] | Kevin Keasey[3] | Peng Li[4] | Danilo V. Mascia[3]

[1]Centre for Advanced Studies in Finance (CASIF), Leeds University Business School, University of Leeds, Leeds, UK | [2]Faculty of Business, Ain Shams University, Cairo, Egypt | [3]International Banking Institute, Leeds University Business School, University of Leeds, Leeds, UK | [4]School of Management, University of Bath, Bath, UK

Correspondence: Danilo V. Mascia (d.v.mascia@leeds.ac.uk)

Received: 15 February 2025 | **Revised:** 14 July 2025 | **Accepted:** 17 July 2025

Funding: The authors received no specific funding for this work.

Keywords: disagreement | ESG ratings | trading volume | uncertainty

ABSTRACT

Given the scale of ESG ratings disagreement, we examine its impact on trading behaviour and find that a one standard deviation increase in disagreement leads to a 1.3% decline in abnormal trading volume, suggesting ESG disagreement introduces uncertainty rather than belief divergence. This effect holds across various robustness tests and is stronger for firms with low ESG performance, limited analyst coverage, or high volatility. The relationship becomes more pronounced after 2016 and is driven by norm-constrained institutional investors. Disagreement is also associated with wider bid-ask spreads, indicating reduced information efficiency.

JEL Classification: G1, G12, G24, M14

1 | Introduction

Environmental, Social, and Governance (ESG) ratings play an increasingly important role in guiding investment decisions, with global assets under ESG management growing from $13 trillion to $30.3 trillion between 2012 and 2022 (Global Sustainable Investment Alliance 2022). As more investors incorporate ESG factors, demand for high-quality ESG information has also risen (Lizárraga 2022)—a key source of ESG information being corporate ESG ratings. However, a well-documented challenge is the lack of agreement among rating agencies. Different ESG rating providers often assign markedly different scores to the same firm and research indicates that disagreements over ESG ratings have been increasing across time (Christensen et al. 2022). On average, ESG ratings from different agencies show a moderate correlation of 0.46 (Avramov et al. 2022; Christensen et al. 2022; Gibson Brandon et al. 2021), reflecting divergent evaluations of companies' ESG performance. This study fills a key gap in the literature by examining how ESG ratings disagreement influences trading behaviour, as measured by trading volume, and by disentangling the roles of uncertainty versus belief divergence in driving that behaviour.

This divergence in ESG assessments, often termed "ESG ratings disagreement", creates significant uncertainty for investors. Conflicting sustainability signals can undermine the credibility of ESG metrics, as the low correlation and opaque methodologies have led some to question the value of these ratings (Halper et al. 2023). For institutional investors, understanding the market impact of ESG ratings disagreement is critically important. Disagreement introduces ambiguity around firms' sustainability profiles, potentially distorting risk assessments, investment valuations, and portfolio construction processes. By identifying how ESG ratings divergence affects trading behaviour, especially the reduction in trading volume driven by uncertainty, our findings provide actionable insights for asset managers, pension funds, insurance companies, and other institutional investors seeking to integrate ESG considerations effectively while managing liquidity and valuation risks. ESG ratings disagreement can serve as a signal to adjust exposure, conduct deeper due diligence, and reassess liquidity risk models in ESG-integrated strategies.

From a regulatory and policy perspective, our results highlight the pressing need for greater transparency, standardisation, and harmonisation of ESG rating methodologies. Policymakers aiming to support sustainable finance must recognise that ESG ratings divergence not only affects firm-level investment decisions but also has broader capital market implications, including reduced market participation, heightened uncertainty, and greater trading frictions. Addressing ESG ratings inconsistency would enhance the efficiency and reliability of ESG markets, ultimately enabling investors to better align capital allocation with sustainable development goals. Enhanced disclosure, clarity of methodologies, and oversight of ESG rating providers could mitigate the noise and confusion that currently impairs market functioning.

Against this backdrop, it is crucial to understand how investors actually respond when faced with divergent ESG information, and what this implies for financial markets and sustainability objectives. For example, previous literature has identified ESG ratings disagreement as a significant barrier to the advancement of sustainable finance. Studies such as Avramov et al. (2022) and Gibson Brandon et al. (2021) provide evidence that higher levels of disagreement among ESG ratings are linked to increased costs of capital, even for environmentally friendly firms. This elevated cost of capital hinders green firms' capacity to undertake new investment initiatives, thereby also limiting the ability of financial markets to effectively support sustainability-oriented investment goals.

Prior research has made progress in documenting the existence and causes of ESG rating disagreements (Berg et al. 2022c; Christensen et al. 2022; Kimbrough et al. 2024) but most studies have focused on price-based outcomes examining, for example, whether firms with higher ESG rating divergence face different stock returns or risk premia. Indeed, emerging evidence suggests that greater ESG rating disagreement can command a higher expected return (lower valuations), consistent with investors demanding a premium for bearing the extra uncertainty or risk (Gibson Brandon et al. 2021).

While such return effects are informative, they provide an incomplete picture of investor behaviour. In theory, ESG rating disagreement can trigger two opposing responses among investors that price outcomes alone may mask. On the one hand, conflicting ESG signals heighten uncertainty about a firm's true sustainability performance, which may cause some risk-averse investors to disengage or delay trading due to ambiguity aversion (De Castro and Chateauneuf 2011; Easley and O'Hara 2009; Easley and O'Hara 2010). On the other hand, the same divergence in opinions can spur other investors to trade more aggressively, as optimists and pessimists rebalance their portfolios based on their disparate beliefs (e.g., Booker et al. 2023; Carlin et al. 2014; Cookson and Niessner 2020; Li and Li 2021). These dual forces, namely cautious withdrawal by some and speculative trading by others, can offset each other in terms of net price movement, rendering the return response subtle or mixed. Trading volume, by contrast, directly captures the intensity of buying and selling activity and is, therefore, a more revealing metric in this context. Unlike returns, an increase in volume can occur even if prices do not move much, possibly reflecting 'busy' two-way trading; or conversely, a drop in volume may signal investors 'sitting on the sidelines'. By focusing on trading volume as the response variable, it is possible to observe both the dampening effect of uncertainty and the amplifying effect of heterogeneous beliefs in the face of ESG rating disagreement.

More specifically, prior research has consistently shown that trading volume is a more effective indicator of investors' reactions to public information than movements in absolute returns. Cready and Hurtt (2002) provide evidence that trading volume outperforms returns in capturing how investors respond to public disclosures. This concept originates from the seminal work of Beaver (1968), who argued that trading volume reflects the variation in individual investor expectations, whereas price changes represent the average expectation across the market. As a result, trading volume offers deeper insight into investor disagreement (Bamber et al. 2011). More broadly, trading volume captures shifts in belief heterogeneity (Barron et al. 2018). It reflects both changes in prior beliefs and varied interpretations of new information. The former refers to the trading activity that occurs as investors adjust their views until reaching a consensus on the new market price. The latter accounts for trading that is unrelated to absolute price changes, as discussed by Kandel and Pearson (1995) and Kim and Verrecchia (1997).

In the context of ESG information, particularly when it is asymmetric, investors are more likely to form differing interpretations of firms' ESG performance (Cookson et al. 2022; Kimbrough et al. 2024). These divergences in belief occur independently of price changes and, therefore, are not captured by return-based measures. Instead, trading volume is uniquely positioned to reveal these differences, as it captures trading behaviour driven by heterogeneous interpretations of asymmetric information, even when there is no movement in price.

We use data from three prominent ESG rating providers, that is MSCI-IVA, LSEG-ESG (formerly Refinitiv) and Sustainalytics, and measure trading behaviour via abnormal trading volume. The data comprise 59,499 firm-month observations across 1303 firms from 2009 to 2022. Our primary finding is that a one standard deviation increase in ESG ratings disagreement corresponds to a 1.3% decrease in abnormal (excess) trading volume. This result is robust to other measures of trading behaviour and various testing procedures. Our findings document that disagreement among ESG ratings' agencies introduces uncertainty rather than belief heterogeneity among investors (Ter Ellen et al. 2019). This is evident by its negative trading impact documented in our findings. To rule out reverse causality (i.e., that low trading volume may itself contribute to greater ESG ratings disagreement), we also test whether lagged trading volumes can predict ESG ratings disagreement for both high and low trading volume groups. We find statistically insignificant results across both sub-samples, suggesting that reverse causality is not an issue in our setting.

We then test whether the relation between ESG ratings disagreement and trading volume evolves over time. We find no evidence of a significant relation in the earlier period of our sample (2009–2016), while the relationship becomes significant in the later part (2017–2022), suggesting that ESG ratings disagreement has become increasingly salient to investors. Furthermore, we show that ESG ratings disagreement is positively associated with information uncertainty as proxied by analyst forecast dispersion.

In addition to the unconditional relation between ESG ratings disagreement and trading volumes, we study how the relationship varies across different market settings. In our sample-split analyses by analyst coverage and market volatility, we show that the ESG disagreement–trading volume relationship is more prominent for firms with low analyst coverage and during periods of high market volatility. We then examine how cross-sectional variations in firms' average ESG performance influence this relationship. Our findings reveal that the negative impact of disagreement on trading is more pronounced when the disagreement concerns firms with low average ESG performance; as average ESG performance improves, the negative effect diminishes in both economic and statistical significance. For firms in the top quartile of average ESG performance, the relationship turns positive. This suggests that investors are more likely to exit (or reduce trading) when disagreement centres on low ESG performance and are more likely to engage (or increase trading) when the disagreement involves firms with strong ESG profiles.

We also investigate the role of heterogeneity in ESG investment objectives among institutional investors in shaping trading volume responses to ESG ratings disagreement. Our analysis indicates that institutional investors constrained by social norms (such as pension funds, university endowments, insurance companies, etc.) are the primary drivers of the negative relationship between ESG disagreement and trading. This highlights the importance of institutional investor objectives in mediating market reactions to ESG ratings disagreements. Conversely, activist investors, despite their growing prominence in ESG engagement, do not appear more sensitive to disagreement than other investors.

Finally, we explore the implications of ESG ratings disagreement for market efficiency. We find a positive relationship with bid-ask spreads, indicating that greater disagreement is associated with higher transaction costs and reduced information efficiency, suggesting a potential impairment of overall market functioning.

Our study contributes to several strands of literature. First, we add to the ESG disagreement literature by documenting its capital market implications (Avramov et al. 2022; Christensen et al. 2022; Gibson Brandon et al. 2021; Kimbrough et al. 2024; Serafeim and Yoon 2023). Second, our work aligns with the broader literature on the value relevance of ESG information (Demetriades and Politsidis 2025; Dhaliwal et al. 2011; Dhaliwal et al. 2012; Heinkel et al. 2001; Pástor et al. 2021), as well as research focusing specifically on the value relevance of ESG ratings (Berg et al. 2022a; Berg et al. 2022c; Berg et al. 2023; Danisman and Tarazi 2024; Rzeźnik et al. 2022; Shanaev and Ghimire 2022). Third, we contribute to the extensive body of work examining the impact of disagreement on trading activity (e.g., Banerjee and Kremer 2010; Cookson and Niessner 2020; Diether et al. 2002; Harris and Raviv 1993; Hong and Stein 2007; Kandel and Pearson 1995; Kim and Verrecchia 1991, 1997; Sprenger et al. 2014; Varian 1985).

By empirically demonstrating how ESG ratings disagreement influences trading activity, our study bridges the ESG and trading behaviour literatures. This study underscores the significant role of ESG ratings in shaping market behaviour and highlights the need for clear and consistent ESG rating standards. More specifically, our findings carry important practical implications for investors and policy-makers. For institutional investors and asset managers, understanding the nuanced impact of ESG ratings disagreement can inform portfolio strategy and risk management. A high divergence in ESG ratings should be treated as a cautionary signal: it indicates greater uncertainty about a firm's ESG performance, which may warrant more careful due diligence and potentially a higher risk premium. At the same time, such divergence could lead to increased market volatility and trading opportunities, as differing investor views play out in the market. Portfolio managers might thus consider ESG disagreement as a factor in liquidity risk and be mindful that heavy trading volume around ESG controversies or rating disagreements could affect stock liquidity and execution costs. Importantly, our results also support the case for regulatory and industry initiatives to improve ESG rating transparency and consistency. If ESG ratings were more harmonised and their methodologies more openly disclosed, investors would face less ambiguity and be less prone to the confusion and reactive trading that divergence can induce.

In other words, reducing the "noise" in ESG ratings could mitigate both the disengagement of sceptics and the speculative trading of optimists, leading to more stable incorporation of ESG information into prices. By shedding light on the consequences of ESG ratings disagreement, this study underscores the need for on-going efforts by regulators, standard setters, and rating agencies to enhance the reliability of ESG metrics. Such efforts would not only help investors make more informed sustainable investment decisions but also contribute to more efficient market outcomes in the era of ESG-integrated finance.

Overall, our study provides timely evidence on how *"aggregate confusion"* in ESG rating translates into real trading behaviour. By distinguishing investor responses driven by uncertainty from those driven by belief divergence, we offer a more nuanced understanding of the interplay between ESG information and market dynamics. This advances the literature on sustainable finance by filling a crucial gap, illustrating the behavioural and market liquidity implications of ESG rating disagreements and guides both investors and regulators in navigating the challenges posed by the current ESG ratings ecosystem.

The rest of the paper is structured as follows. Section 2 provides a background, a discussion of ESG ratings disagreement and develops the main hypotheses. Section 3 describes the research design and the data, while Section 4 presents the results. Section 5 offers conclusions.

2 | Background, ESG Ratings Disagreement, and Hypotheses

2.1 | Background

ESG is a recently developed framework that has rapidly gained momentum in financial markets. Despite being relatively new, ESG falls under the broad umbrella of sustainable investing and has roots back to the earlier socially responsible investing (SRI) and corporate social responsibility (CSR) concepts. Since its early emergence and up until now, research studies examining the implications of such a framework on return performance provide mixed results (Avramov et al. 2022). To resolve this issue, Starks (2023) recommends disaggregating investors' preferences towards ESG factors and, therefore, their performance expectation from them by classifying ESG investors as either "values" or "value" investors. "Values" investors seek non-pecuniary benefits as making a positive impact towards the environment and the society. However, "value" investors seek lower risk or higher returns from ESG analysis. This is consistent with the CFA Institute's definition of ESG as "finding value in firms – not just supporting a set of values" as in SRI or CSR (CFA Institute 2024).

The alignment of the ESG framework with the preferences of "value" investors supports Edmans (2023) argument that there is no such thing as "ESG investing"; rather, the integration of ESG factors should be viewed as "ESG analysis." This perspective treats ESG as one of many risk factors considered in investment valuation, making it consistent with traditional investing practices. ESG analysis involves incorporating additional, material factors that enhance financial analysis and lead to more accurate assessments of a firm's fundamentals. These factors may affect a firm's risk and return profile and are often not yet fully priced into the market. In contrast, SRI and CSR align more closely with the goals of "values" investors, as they intentionally move away from the conventional risk-return framework in favour of ethical or normative considerations.

The incorporation of ESG factors alongside conventional financial analysis to enhance risk-adjusted returns is known as "ESG integration", which is one of several ESG investing approaches. Other approaches include ESG screening, thematic investing, impact investing, and stewardship.[1] ESG integration involves the use of ESG factors in both investment analysis and decision-making processes, with the primary goal of achieving superior risk-adjusted returns (Global Sustainable Investment Alliance, Principles for Responsible Investing, and CFA Institute 2024). Unlike other approaches, ESG integration does not impose any constraints on portfolio construction and can be applied by all investors, regardless of their motivations or preferences, and across various ESG investing strategies. It is equally applicable to non-ESG investors when evaluating a firm's risk-return profile. As such, ESG integration is considered a motivation-neutral approach that does not introduce an additional objective optimisation problem (Pedersen et al. 2021).

ESG integration in investment analysis begins with the identification of material ESG issues relevant to firms and their industries. This is followed by an evaluation of their impact on the firm's risk-return profile. Integrating ESG with financial analysis helps uncover risks and opportunities that may not be fully captured or priced by the market. In equity analysis, ESG data are incorporated alongside traditional factors such as SMB, HML, momentum, and volatility. This integration typically results in adjustments to key valuation parameters—such as forecasted cash flows, discount rates, and terminal values in discounted cash flow models—or to valuation multiples in relative valuation models. ESG integration also plays a role in investment decision-making during asset allocation, security selection, and portfolio construction, particularly when ESG analysis leads to a reassessment of a firm's fair value (Global Sustainable Investment Alliance, Principles for Responsible Investing, and CFA Institute 2024).

ESG ratings, provided by third-party agencies, evaluate how effectively companies manage ESG risks and opportunities. These ratings serve as a summary measure of ESG performance, akin to how net income summarises financial outcomes (Christensen et al. 2022). They are widely used by investors to incorporate ESG considerations into investment strategies, with the goal of achieving better risk-adjusted returns. By focusing on financially material ESG issues, these ratings appeal to all investors, not just those explicitly pursuing ESG goals. Typically, ESG ratings reflect both a firm's exposure to ESG risks and its ability to manage these risks through policies and initiatives, with higher ratings indicating stronger management.

Third-party ESG ratings are among the most widely used sources of ESG information in sustainable investing (Brock et al. 2023). While final ratings and scores are key outputs, they represent only part of the information provided by rating agencies. These ratings are underpinned by detailed analysis and scoring across the three ESG pillars: Environmental, Social, and Governance. Agencies also evaluate performance on specific key issues within each pillar, assigning scores accordingly. In addition, a range of performance metrics and indicators are used to calculate these key issue scores (LSEG 2024; MSCI 2024b; Sustainalytics 2024).

Investors can utilise the final ESG ratings, aggregated scores at the pillar or key issue level, or specific metrics, such as carbon intensity per USD of revenue, in their investment analysis and decision-making processes. Increasingly, ESG rating agencies are adopting an ESG integration approach when calculating scores. This approach emphasises the identification and assessment of material ESG risks and opportunities, as well as how effectively companies manage them. By focusing on financially material ESG factors, this methodology enables investors to incorporate ESG insights into their broader investment analysis and decision-making processes, aiming for better risk-adjusted returns. As a result, ESG ratings are particularly well-suited to meet the needs of investors pursuing an ESG integration strategy.

ESG rating agencies' emphasis on ESG integration reflects the need to support the large investor base that adopts this approach in their ESG investing strategies. According to the Global Sustainable Investment Alliance (GSIA), ESG integration has been the dominant ESG investment strategy over the past decade. The GSIA's biennial *Global Sustainable Investment*

Report highlights that ESG integration leads all ESG strategies, with $25 trillion in assets under management in 2020. This is followed by negative screening ($15 trillion) and stewardship strategies ($10.5 trillion) (Global Sustainable Investment Alliance 2022). ESG integration can be implemented as a standalone investment strategy or used alongside other approaches, such as portfolio optimisation (MSCI 2024a). Since the objectives and methodologies of most ESG rating agencies are grounded in the ESG integration framework, this underlines the potential for widespread use of ESG ratings in financial markets and their influence on various market outcomes.[2]

Most investors conduct in-house ESG analysis using a variety of information sources, including third-party ratings. A key resource in this process is the decision-useful data and metrics provided by rating agencies beyond the often-criticised final aggregated scores, which are considered to be noisy and less informative (Berg et al. 2022a; Berg et al. 2022c). This critique can potentially diminish the perceived value of final ratings in investment analysis and decision-making, and thereby reduce their influence on financial markets. Nevertheless, even when investors disregard aggregated final scores or pillar-level summaries, scores for individual key issues remain highly relevant, particularly when investors are targeting specific ESG dimensions in alignment with their investment goals. These key issues—such as biodiversity, water stress, and carbon emissions (within the environmental pillar), or workplace safety, human rights, and product responsibility (within the social pillar)—are embedded in the broader analysis conducted by rating agencies and contribute to the formulation of final scores.

Rating providers assign weights to ESG key issues based on their relevance to each industry (materiality). They assess the associated risks and opportunities, quantify firms' exposure to these factors, evaluate how effectively firms manage them, and then calculate a key issue score. This score reflects both a firm's exposure to and management of each material ESG issue (LSEG 2024; MSCI 2024b; Sustainalytics 2024). Essentially, the key issue score indicates how well a firm handles its exposure to material ESG risks and opportunities. Stronger management suggests lower risk and improved financial performance, aligning with the goals of ESG integration strategies. Furthermore, final aggregated ESG scores, along with scores for the three ESG pillars, are derived from these key issue scores and their respective materiality weights. While some (Flood 2020; Larcker et al. 2022b) argue that final aggregated scores should not be heavily relied upon by investors, or serve merely as a general indicator, they still encapsulate the underlying key issue scores and metrics. These data points remain integral to investor analysis and decision-making processes.

According to Brock et al. (2023), although firms may be rated by more than ten ESG rating agencies, investors typically rely on just one to three as their primary sources of ESG information. Alongside other data, these ratings shape investors' judgements about which ESG issues represent material risks or opportunities to include in their analysis. Investors assess how these risks and opportunities may impact cash flows, idiosyncratic risks, and systematic risks. Based on this assessment, investors adjust their valuation model parameters. For instance, they may alter the discount rate when facing higher systematic ESG risks, increase the growth rate when anticipating ESG-driven opportunities that boost future cash flows, or modify terminal value assumptions. Portfolio exposure weights may also be adjusted to account for elevated diversifiable idiosyncratic risks, such as extreme ESG events or tail risks. The integration of ESG ratings and scores is not limited to fundamental strategies; it also extends to quantitative approaches, strategies guided by third-party analyst recommendations, and those that use ESG ratings to inform asset allocation decisions across asset classes and countries. Additionally, ESG ratings are employed in security selection within no-tracking-error or low-tracking-error indexing strategies (Global Sustainable Investment Alliance, Principles for Responsible Investing, and CFA Institute 2024). Furthermore, the top three asset management firms, BlackRock, Vanguard, and Fidelity, employ third-party ratings within their ESG investment approaches (BlackRock 2024; Fidelity 2024; Vanguard 2023).[3]

2.2 | ESG Ratings Disagreement

The rise of ESG investing has brought with it a range of new market challenges, chief among them being the inconsistencies among third-party ESG rating agencies. Discrepancies in ESG ratings have sparked concern in both academic research and practical investment contexts, as they can mislead investors, complicate fund managers' disclosure obligations, and disincentivize companies from improving their ESG performance (Larcker et al. 2022a). Additionally, such inconsistencies can weaken the link between ESG performance and expected financial returns, thereby influencing firms' cost of capital and potentially limiting their future growth prospects (Berg et al. 2022a).

The extent to which ESG rating disagreements influence trading behaviour largely depends on the perceived value relevance of ESG information. Theoretical models, such as those by Heinkel et al. (2001), propose that reduced investor demand for non-ESG-compliant stocks raises their cost of capital compared to ESG-aligned firms. Empirical findings support this theory; Demetriades and Politsidis (2025), for instance, report that loan spreads are 7.3% higher for fossil fuel companies. Similarly, Cornell (2021) and Pástor et al. (2021) argue that investors seeking non-financial (non-pecuniary) benefits contribute to a lower cost of capital for ESG-compliant firms. Additional empirical research confirms the growing integration of ESG data into firm valuations, analyst forecasts, and assessments of systematic risk (Bax et al. 2024; Dhaliwal et al. 2011; Dhaliwal et al. 2012). Investors are increasingly shown to incorporate ESG metrics alongside traditional financial information in their decision-making processes (Moss et al. 2022).

ESG ratings, which are derived from the analysis of hundreds of ESG metrics per firm, represent a key source of ESG-related information. Leading ESG rating agencies include MSCI-IVA, Sustainalytics, and LSEG-ESG, all of which are featured in the "Rate the Raters" survey by the SustainAbility Institute (Brock et al. 2023). Among them, MSCI-IVA and Sustainalytics are particularly influential, with their ratings commonly used by ESG-focused mutual funds to guide investment decisions (Berg et al. 2022a). LSEG-ESG's ratings are also frequently referenced in research examining ESG rating disagreement (Avramov et al. 2022; Christensen et al. 2022). Empirical evidence indicates that changes in ESG ratings, especially those issued by Sustainalytics, can prompt significant market reactions (Rzeźnik et al. 2022). Rating downgrades, in particular, have been associated with negative asset returns (Shanaev and Ghimire 2022), and broader shifts in ESG scores have been shown to influence asset prices over time (Berg et al. 2022a; Rzeźnik et al. 2022). However, the presence of disagreement among rating agencies can introduce noise into these signals, potentially distorting market interpretations and affecting trading behaviour (Berg et al. 2022c).

Despite their widespread use, ESG ratings exhibit considerable disagreement. The average correlation between ratings from different providers is only 0.46, far lower than the 0.92 correlation typically observed among credit ratings (Berg et al. 2022b). This disagreement arises for several reasons. Berg et al. (2022b) identified three primary drivers: scope (differences in the ESG attributes being measured), measurement (variations in the indicators used to assess the same attribute), and weighting (the importance assigned to each attribute). Measurement differences account for the largest share of disagreement (56%), followed by scope (38%) and weighting (6%). They also noted a “rater effect,” where methodological biases unique to each rater contribute to disagreement.

Disclosures also play a role in ESG disagreement. Christensen et al. (2022) found that greater ESG disclosures, measured by Bloomberg ESG scores, were associated with increased disagreement, likely due to varying interpretations of the disclosed information. However, Kimbrough et al. (2024) reported the opposite: increased ESG disclosures, analysed through textual content, led to reduced disagreement. Other factors influencing disagreement include firm characteristics (e.g., size, profitability, and industry), the tone and wording of sustainability reports, and adherence to ESG standards such as the Global Reporting Initiative (GRI) (Gibson Brandon et al. 2021; Kimbrough et al. 2024).

Beyond identifying the causes of ESG rating disagreement, a significant body of literature has also examined its market consequences. Gibson Brandon et al. (2021) investigate the effect of ESG rating disagreement on stock returns. Analysing monthly stock returns for a sample of S&P 500 firms from 2010 to 2017, they find a significant positive relationship between ESG disagreement and stock performance. This finding is explained through theoretical models in which disagreement represents a form of uncertainty, prompting investors to demand higher expected returns. Similarly, Avramov et al. (2022) demonstrate that the negative relationship between ESG performance and stock returns weakens, and can even reverse to positive, for stocks with high levels of ESG disagreement. Using institutional investors' holdings as a proxy for investor demand, they also find that investor demand for a firm's stock declines as ESG rating disagreement increases. These findings emphasise the asset pricing implications of ESG rating divergence.

Further documented consequences include increased return volatility, higher cumulative abnormal returns, reduced access to equity and debt financing, and greater reliance on internal financing (Christensen et al. 2022). Serafeim and Yoon (2023) add that ESG disagreement dampens the market's response to ESG-related news. A closely related study by Kimbrough et al. (2024) finds that ESG disagreement is positively associated with broader capital market uncertainty and disagreement. Specifically, they document a positive relationship between ESG disagreement and analyst forecast dispersion, stock return volatility, and bid-ask spreads. Building on these insights, our study explores the effect of ESG rating disagreement on a key capital market dimension: trading activity. A more detailed discussion of the foundations of disagreement models can be found in Appendix A.

2.3 | Hypotheses

We build on existing research into ESG ratings disagreement by examining its influence on trading volume. In a Bayesian learning framework, investors start with prior beliefs and update them after observing public signals, such as information about a firm's value. Disagreement among investors can arise from three key sources in this process (Xiong 2013):

1. Different prior beliefs—Investors have varying initial perspectives.
2. Asymmetric information—Investors observe different signals.
3. Differential interpretations—Investors observe the same signals but update their beliefs differently based on personal models.

When valuing firms, investors often rely on one or more ESG ratings. Due to the growing importance of ESG information, disagreement can emerge when investors encounter conflicting ESG signals from multiple ratings (asymmetric information) (Cookson and Niessner 2020). This disagreement makes investors uncertain about the precision of firms' ESG performance signals (Acemoglu et al. 2016). A combination of differing prior beliefs and uncertainty about public signals can amplify disagreement, even when the same information is available to all (Armstrong et al. 2024). Therefore, disagreement among investors about ESG performance may arise from uncertainty.

High levels of disagreement often create ambiguity, making it difficult for investors to confidently assess future events. This type of uncertainty, as described by Knight (1921), can discourage trading or even lead to non-participation (De Castro and Chateauneuf 2011; Easley and O'Hara 2009). When investors are unable to rank or prioritise investment choices due to incomplete preferences, uncertainty reduces trading activity (Easley and O'Hara 2010). Empirical evidence supports this view, showing that uncertainty negatively affects trading volume (Armstrong et al. 2024; Palley et al. 2024).

Zhang (2006b) defines information uncertainty as ambiguity about how new information affects a firm's value, stemming from two sources: volatility in a firm's fundamentals and poor-quality information. For ESG ratings, this can be attributed to both high volatility in underlying ESG fundamentals and insufficient high-quality information. Thus, ESG ratings disagreement can be viewed as a mix of volatility of a firm's actual ESG performance and an error term capturing information quality (Zhang 2006a). Given the volatility and information gaps in ESG assessments (Larcker et al. 2022b), we argue that ESG ratings disagreement leads investors to become uncertain about their valuations of firms. This uncertainty reduces their willingness to "agree to disagree", a key condition for trading to occur. Therefore, we hypothesise:

H1. *ESG ratings disagreement is negatively associated with abnormal trading because it increases investor uncertainty.*

Alternatively, ESG disagreement among investors may be caused by belief heterogeneity rather than uncertainty. Investors' beliefs diverge when they are exposed to different information sets (Cookson and Niessner 2020). This is either because of gradual information flows and limited attention (Hong and Stein 2007) or overconfidence (Xiong 2013). In contrast to the negative trading impact of uncertainty, belief heterogeneity encourages trading as it creates a scope for transactions between investors (Ter Ellen et al. 2019). The positive disagreement-trading relationship is also supported empirically (Booker et al. 2023; Carlin et al. 2014; Cookson and Niessner 2020; Li and Li 2021; Sprenger et al. 2014). Based on this reasoning, we propose that ESG ratings disagreement increases trading and hypothesise:

H2. *ESG ratings disagreement is positively associated with abnormal trading driven by belief heterogeneity.*

3 | Research Design and Data

3.1 | Variable Measurement

3.1.1 | Abnormal Trading Volume

In examining the effect of ESG ratings disagreement on trading behaviour, we focus on abnormal trading volume as it is widely used (e.g., Booker et al. 2023; Cookson and Niessner 2020; Kandel and Pearson 1995; Li and Li 2021). For robustness, we use the gross trading volume in Section 4.1 (Bamber et al. 2011).

Investors trade for various reasons, primarily for liquidity needs or due to disagreement (opinion divergence). To isolate disagreement-driven trading, we control for liquidity trading by detrending the volume data. Our calculation of detrended (abnormal) trading volume is based on prior literature (Booker et al. 2023; Cookson and Niessner 2020). Using monthly volume and shares outstanding data from CRSP, we first calculate monthly turnover as the trading volume divided by shares outstanding for each firm-month. We then take the natural logarithm of this turnover. To control for liquidity trading, we detrend the log of turnover by subtracting its median over the period t–7 and t–2 (6 months after skipping month t–1), resulting in the abnormal log turnover ($AbLogTurnover_{i,t}$):

$$\text{AbLogTurnover}_{i,t} = \ln\left(\text{Turnover}_{i,t}\right) - \text{median}\left[\ln\left(\text{Turnover}_{t-7,t-2}\right)\right]. \tag{1}$$

As an alternative measure for abnormal trading, we follow Garfinkel (2009) and Barron et al. (2018). This measure, called Abnormal Market-Adjusted Log Turnover ($AbMaLogTurnover_{i,t}$), is designed to capture unusual trading activity controlling for market-wide trading volume. Tkac (1999) provides empirical support for such adjustment when calculating information-related trading. Similar to $AbLogTurnover_{i,t}$, we use monthly data on trading volume and shares outstanding from CRSP. For each firm-month, we calculate the turnover by dividing the monthly trading volume by the number of shares outstanding. To adjust for overall market volume trends, we calculate turnover across all our sampled firms in each month, take its natural logarithm, and then subtract this value from the log turnover of each firm-month. This gives us the market-adjusted log turnover, which reflects abnormal trading behaviour relative to typical market activity:

$$\text{MKT\_ADJ\_Turnover}_{i,t} = \ln\left[\frac{\text{Volume}_{i,t}}{\text{Shares Outstanding}_{i,t}}\right] - \ln\left[\frac{\text{Volume}_{t}}{\text{Shares Outstanding}_{t}}\right]_{mkt}. \tag{2}$$

To account for liquidity trading, we detrend the market-adjusted log turnover by deducting its median over the period t–7 and t–2 (6 months after skipping month t–1) which provides the abnormal market-adjusted log turnover ($AbMaLogTurnover_{i,t}$):

$$\text{AbMaLogTurnover}_{i,t} = \left[\text{MKT\_ADJ\_Turnover}_{i,t}\right] - \text{median}\left[\text{MKT\_ADJ\_Turnover}_{t-7,t-2}\right]. \tag{3}$$

3.1.2 | ESG Ratings Disagreement

Consistent with Avramov et al. (2022), we measure ESG ratings disagreement as the average pairwise standard deviation of monthly ESG score percentiles for each firm, based on the three raters: MSCI-IVA, LSEG-ESG (formerly Refinitiv), and Sustainalytics. This approach reflects the common practice among investors of relying on two to three ESG raters when evaluating firms' ESG performance (Brock et al. 2023). These rating agencies focus on assessing firms' management of financially material ESG risks and opportunities, aligning with the priorities set by the International Accounting Standards Board (SASB 2024). We focus on these three agencies for the following reasons:

1. Aggregating multiple ESG ratings, as in prior studies, overlook the very diverse objectives of these ratings (i.e., what they measure) and the varied ESG investing goals of investors who use them (Starks 2023).
2. According to the institutional investors survey by Brock et al. (2023), investors typically rely on two or, at most, three rating agencies to assess ESG performance. Based on the same survey, these agencies are highly regarded by institutional investors for both quality and usefulness.
3. The three rating agencies, namely MSCI-IVA, LSEG-ESG, and Sustainalytics, are widely used in the ESG disagreement literature (Avramov et al. 2022; Berg et al. 2022b; Christensen et al. 2022; Gibson Brandon et al. 2021; Serafeim and Yoon 2023).

The three agencies share a common objective: to evaluate how well firms manage ESG issues. They adopt the concept of financial materiality, assessing which ESG issues materially affect firm value within each specific industry or firm. Both MSCI-IVA and Sustainalytics break down their ESG scores into two components, namely exposure and management, and calculate the final score as the difference between these two, representing either how much exposure the firm has managed (MSCI-IVA) or how much exposure remains unmanaged (Sustainalytics) (MSCI 2024b; Sustainalytics 2024). Sustainalytics scores indicate unmanaged ESG risks and opportunities, meaning that a higher score reflects poorer performance. Conversely, MSCI-IVA scores represent managed components, where a higher score indicates a better impact on the firm's risk-return profile and fundamental value. To align Sustainalytics' scores with MSCI-IVA's, we adjust the Sustainalytics score by multiplying it by −1 and adding 100, following Berg et al. (2023). This adjustment reflects the managed risks and opportunities, consistent with MSCI-IVA's scoring system.

MSCI-IVA's ESG scores are on a scale from 1 to 10, while Sustainalytics does not have a fixed scale, starting from zero and potentially reaching any value. Our adjustment of Sustainalytics scores caps them at 100. To align the two scales, we adjust MSCI-IVA scores by multiplying by 10, following Christensen et al. (2022), resulting in an MSCI-IVA score range of 1–100, consistent with Sustainalytics. LSEG-ESG scores are also scaled from 1 to 100 and assess firms' ESG performance relative to peers using a percentile ranking. LSEG-ESG applies the materiality concept differently, using disclosure levels as indicators of ESG issue importance and calculating a proprietary materiality matrix (LSEG 2024).

For comparability, we convert all adjusted scores from the three raters into percentile ranks. Following Avramov et al. (2022), our final measure of ESG ratings disagreement is the average of the pairwise standard deviations of the percentile ranks from the three agencies for each firm-month.[4] We standardise this measure to have a mean of zero and a standard deviation of one (Cookson and Niessner 2020), allowing us to interpret changes in the dependent variable (abnormal trading volume) in terms of unit standard deviation changes in the independent variable (ESG ratings' disagreement).

3.2 | Data and Sample Construction

To build our sample we merge the MSCI-IVA, LSEG-ESG, and Sustainalytics data sets using both date and ISIN identifiers. Each agency provides ESG scores as of the first day of month t, reflecting firms' ESG performance for the preceding month. This approach ensures that the scores are available to market participants, making disagreement among the ratings observable at the start of the month, during which the outcome variable (abnormal trading) is measured. Our sample period begins in August 2009, when Sustainalytics' coverage starts, and ends in December 2022, the point at which we construct the sample.

We link our ESG merged dataset with data on all United States common shares (share codes 10 and 11) listed on the NYSE, AMEX, and NASDAQ (exchange codes 1, 2, and 3) for the sample period. We source turnover, volatility, and bid-ask spread data from CRSP, analyst forecasts, and coverage data from I/B/E/S, institutional ownership data from Thomson Reuters 13F, and firm financial and performance data from Compustat. After extracting the 8-digit CUSIP from the ISIN code in the firm-month ESG merged dataset, we combine it with CRSP, Thomson Reuters 13F, I/B/E/S, and Compustat data sets using both date and the 8-digit CUSIP identifiers. Following the inclusion of all required data,[5] our final main sample comprises 59,499 firm-month observations from 1303 unique firms.[6]

3.3 | Empirical Model

Our study examines the broader impact of ESG ratings disagreement on trading volume responses to all information events within a given period (Ajinkya et al. 1991; Li and Li 2021). To examine the relationship between ESG ratings disagreement and abnormal trading, we estimate the following panel's fixed-effect regression model:

$$\begin{aligned}\text{AbMaLogTurnover}_{i,t} = \beta_0 &+ \beta_1 \text{STD\_ESG\_DISG}_{i,t} \\ &+ \beta_2 \text{AbMaLogTurnover}_{i,t-1} \\ &+ \sum \beta_j \text{ Controls} + \gamma_1 + \gamma_2 + e_{i,t}.\end{aligned} \tag{4}$$

In this model, *AbMaLogTurnover* represents the abnormal (market-adjusted) log turnover, calculated as the difference between the natural logarithm of turnover (or market-adjusted turnover) for firm i in month t and its median over the 6 months period t–7 and t–2. STD_ESG_DISG, our main variable of interest, captures changes in trading arising from ESG ratings disagreement. Similar to Christensen et al. (2022) and Kimbrough et al. (2024), our control variables include Firm Size (SIZE), which proxies for market attention, with the idea being that larger firms attract more attention; Return on Assets (ROA) to control for firm performance; Market-to-Book Ratio (MTB) to capture future growth potential; Leverage (LEV) for capital structure; Institutional Ownership (INST_OWNERSHIP) for ownership structure; Analysts Coverage (ANALYSTS) for the number of analysts following the firm. Furthermore, following Ter Ellen et al. (2019), we also control for Analysts Forecasts Dispersion (Log(DISP)), which proxies for uncertainty; Volatility (VOLATILITY) to control for risk; and Bid-ASK Spread (SPREAD) to control for liquidity. Table A1 in the Appendix A provides a detailed description of our variables. We also control for the first lag of the dependent variable to account for its persistence. γ_1 are firm fixed effects, while γ_2 are month fixed effects. Standard errors are clustered at the firm level to adjust for cross-sectional autocorrelation and heteroscedasticity.

3.4 | Descriptive Statistics

Panel A of Table 1 presents descriptive statistics. The main dependent variable, abnormal log turnover (*AbLogTurnover*), has a mean of 0.005 and a median of −0.024. The other measure for abnormal trading is abnormal market-adjusted log turnover (*AbMaLogTurnover*) and has a mean of −0.003 and median −0.025. Gross turnover (*Turnover*) has mean of 0.231 and a median of 0.168.

Our main independent variable for testing both hypotheses, ESG ratings disagreement (ESG_DISG), is the average of pairwise standard deviation between the percentile ranks of the ratings provided by the three agencies (MSCI-IVA, LSEG-ESG, and Sustainalytics) for each firm in each month during the sample period. ESG_DISG has a mean of 14.17 and a median of 13.79, which is consistent with the average ESG ratings disagreement reported in the literature: 12.3 (Christensen et al. 2022), 19.1 (Kimbrough et al. 2024), and 20 (Gibson Brandon et al. 2021). STD_ESG_DISG is the standardised value of ESG_DISG and has a mean of −0.003 and a median of −0.062.

To provide further context on the construction and representativeness of the sample, Panel B of Table 1 reports the sectoral distribution of firm-month observations, alongside average values of standardised ESG ratings disagreement by industry, as identified using SIC codes. The total number of observations (59,436) is slightly lower than the full sample size of 59,499 due to 63 firm-month observations with missing SIC codes. Overall, the sample is broadly representative across industries, with the largest share of observations coming from the manufacturing sector (35.2%), followed by wholesale and retail (13.8%), and services (13.3%). Other sectors such as transportation, finance, and mining are also present, supporting a wide industry coverage. The final column reveals substantial variation in ESG disagreement across sectors. Since this measure is standardised around zero, values should be interpreted in relative terms, with negative values indicating lower disagreement and positive values indicating higher disagreement. We observe that disagreement is generally lower in sectors such as mining,

TABLE 1 | Descriptive statistics and sample distribution by industry.

Panel A: Descriptive statistics

This panel presents summary statistics for the main sample. Descriptions of all variables are provided in Table A1 in the Appendix.

Variables	*N*	Mean	Std. Dev.	1st Quartile	Median	3rd Quartile
Turnover	59,499	0.231	0.268	0.115	0.168	0.261
AbLogTurnover	59,499	0.005	0.352	−0.229	−0.024	0.204
AbMaLogTurnover	59,499	−0.003	0.320	−0.208	−0.025	0.173
ESG_DISG	59,499	14.170	6.166	9.664	13.790	18.380
STD_ESG_DISG	59,499	−0.003	0.988	−0.731	−0.062	0.683
SIZE	59,499	8.371	1.819	6.986	8.280	9.630
ROA	59,499	0.010	0.043	0.004	0.018	0.031
MTB	59,499	5.933	9.493	1.853	3.116	5.769
LEV	59,499	0.262	0.185	0.101	0.253	0.390
ANALYSTS	59,499	13.063	8.568	6.000	11.000	19.000
INST_OWNERSHIP	59,499	80.046	15.106	72.166	83.432	91.525
VOLATILITY	59,499	0.025	0.016	0.014	0.020	0.030
SPREAD	59,499	0.001	0.001	0.000	0.000	0.001
Log(DISP)	59,499	−3.206	1.409	−4.234	−3.384	−2.327

Panel B: Sample distribution by industry

This panel reports the sectoral distribution (using SIC codes) of firm-month observations (central columns), alongside average values of standardised ESG ratings disagreement (last column).

	Observations		
SIC description	**Freq.**	**Percent**	**Average disagreement**
Mining	2621	4.41	−0.2528
Construction	1146	1.93	−0.1796
Manufacturing	20,930	35.21	−0.0180
Transportation, communications, electric	5868	9.87	−0.1849
Wholesale, retail	8171	13.75	0.0609
Finance, insurance, real estate	4504	7.58	−0.1696
Services	7880	13.26	0.0473
Public administration	11	0.02	−0.7817
Nonclassifiable	8305	13.97	0.3679
Total	59,436	100.00	

construction, transportation, and finance, while it is higher in wholesale/retail, services, and particularly in nonclassifiable industries.

Consistent with prior research, the median firm in our sample has a quarterly return on assets of 1.8%. On average, firms in our sample have a leverage ratio (total debt to total assets) of 26.2% and a market price-to-book ratio of 5.75. Our sample includes firms covered by the three ESG ratings agencies (MSCI-IVA, LSEG-ESG, and Sustainalytics) and requires that firms be covered by at least two analysts in each firm-month. On average, firms in our sample are covered by 13 analysts, with a median of 11 analysts.

A notable observation in our sample, consistent with prior research (Kimbrough et al. 2024), is the high average institutional ownership percentage of 80%. This highlights the potential association between analyst coverage, institutional ownership, and firm coverage by ESG ratings agencies.

Table 2 presents pairwise correlations. Consistent with the literature, we observe that ESG ratings disagreement tends to be lower for larger firms, as these firms generally have a better information environment. Firms with high ESG ratings disagreement are less profitable and exhibit higher leverage. These firms also tend to have greater future growth opportunities (MTB), more analysts following them, and lower institutional ownership. High ESG ratings disagreement firms have more stock return volatility (more risk), high bid-ask spread (less liquidity), and more dispersion among analysts' earnings per share (EPS) forecasts (more uncertainty).

4 | Empirical Results

4.1 | Results for Tests of H1 and H2

Table 3 presents our baseline results for estimating Equation (4) to test hypotheses H1 and H2. Using a panel regression with firm and month fixed effects, our results show a negative and statistically significant relationship between ESG ratings disagreement and abnormal trading.[7] Economically, a one standard deviation increase in ESG ratings disagreement is associated with a 1.3% (1.2%) decrease in abnormal (market-adjusted) trading volume. The control variables display signs and significance levels that align with prior studies focused on the U.S. market (Kimbrough et al. 2024).

The results highlight the role of ESG ratings agencies as an important information intermediary in the market. They suggest that disagreement among ESG raters leads to higher uncertainty about firms' future prospects rather than more heterogeneous beliefs among investors. Such uncertainty leads to less trading volume. The negative association between ESG ratings disagreement and abnormal trading aligns with Hypothesis 1, theoretical predictions about the impact of uncertainty on trading (De Castro and Chateauneuf 2011; Easley and O'Hara 2009; Easley and O'Hara 2010), and prior empirical findings (Armstrong et al. 2024; Palley et al. 2024).[8]

TABLE 2 | Correlation matrix.

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
(1) STD_ESG_DISG	1.000									
(2) SIZE	−0.004	1.000								
(3) ROA	−0.070***	0.370***	1.000							
(4) MTB	0.055***	−0.093***	−0.007*	1.000						
(5) LEV	0.031***	0.191***	0.091***	0.213***	1.000					
(6) ANALYSTS	0.009**	0.594***	0.231***	0.140***	0.016***	1.000				
(7) INST_OWNERSHIP	−0.136***	−0.083***	0.091***	−0.026***	0.018***	−0.016***	1.000			
(8) VOLATILITY	0.124***	−0.376***	−0.409***	0.034***	0.013***	−0.223***	−0.078***	1.000		
(9) SPREAD	0.087***	−0.441***	−0.375***	−0.048***	−0.051***	−0.340***	−0.157***	0.380***	1.000	
(10) Log(DISP)	0.071***	−0.270***	−0.321***	−0.016***	0.038***	−0.206***	−0.098***	0.389***	0.259***	1.000

Note: Significance level at 10%, 5%, or 1% is indicated by *, **, or ***, respectively.

TABLE 3 | ESG ratings' disagreement and abnormal trading volume.

	(1) $\mathbf{AbLogTurnover}_{i,t}$	(2) $\mathbf{AbMaLogTurnover}_{i,t}$
$\text{STD\_ESG\_DISG}_{i,t}$	−0.013***	−0.012***
	(−6.158)	(−6.288)
$\text{AbLogTurnover}_{i,t-1}$	0.430***	
	(96.541)	
$\text{AbMaLogTurnover}_{i,t-1}$		0.473***
		(97.292)
SIZE	−0.021***	−0.020***
	(−3.031)	(−3.524)
ROA	0.136*	0.032
	(1.667)	(0.435)
MTB	0.001***	0.001**
	(2.664)	(2.464)
LEV	−0.202***	−0.171***
	(−8.396)	(−8.233)
ANALYSTS	0.001	0.001
	(1.247)	(1.198)
INST_OWNERSHIP	0.001	0.000
	(1.622)	(0.963)
VOLATILITY	12.572***	8.485***
	(79.185)	(48.977)
SPREAD	−22.387***	−26.966***
	(−10.257)	(−12.715)
Log(DISP)	−0.030***	−0.019***
	(−16.815)	(−12.206)
Firm fixed effects	Yes	Yes
Month fixed effects	Yes	Yes
SE clustered by firm	Yes	Yes
R-squared	0.437	0.323
Firm-months (*N*)	59,499	59,499
Number of firms	1303	1303

Note: This table reports the results of the relationship between ESG ratings' disagreement and two measures of abnormal trading volume, namely abnormal log turnover [Column (1)] and abnormal market-adjusted log turnover [Column (2)]. $\text{AbLogTurnover}_{i,t}$ (Abnormal log turnover) is computed according to Equation (1). $\text{AbMaLogTurnover}_{i,t}$ (Abnormal market-adjusted log turnover) is computed according to Equation (3). $\text{STD\_ESG\_DISG}_{i,t}$ (ESG ratings' disagreement) is the average of the pairwise standard deviations (standardised to have 0 mean and 1 standard deviation) between the percentile ranks of monthly ESG scores provided to each firm by the three ESG rating providers: MSCI-IVA, LSEG-ESG, and Sustainalytics. Control variables are described in Table A1 in the Appendix A. All variables are winsorized at the 1% and 99% levels. Intercept included but not reported. All models include firm and month fixed effects. Standard errors are clustered by firm, and the resultant *t*-statistics are shown in parentheses. Significance level at 10%, 5%, or 1% is indicated by *, **, or ***, respectively.

To further validate our baseline results, we examine whether our findings hold when using an alternative measure of trading activity. In our main analysis, we focus on abnormal (excess) trading to better capture information-based trading. This involves adjusting the gross trading volume, a method commonly used in the literature to reduce measurement errors and concentrate on trading triggered by information events. However, Bamber et al. (2011) highlight that this adjustment is "ad hoc" because there is no clear theoretical basis for deciding whether to adjust or not. Additionally, there is no consensus on how to measure non-information-based trading, and some information-based trading is intertwined with liquidity trading (Admati and Pfleiderer 1988). As a result, excluding non-information (liquidity) trading through detrending may inadvertently remove some of the information-based trading we aim to study.

To address these concerns, we repeat our baseline analysis using gross trading volume without any adjustments. This approach follows the Bamber et al. (2011) recommendation to analyse both adjusted (abnormal) and unadjusted (gross) trading volumes. Supporting Information S1: Table SOA3 in the

Online Appendix shows the results of using gross trading volume measured as the natural logarithm of gross turnover (*LogTurnover*) as the dependent variable in Equation (4). These results confirm our baseline findings: there is a significant negative association between ESG ratings disagreement and trading. This relationship is statistically significant at the 1% level. Economically, a one standard deviation increase in ESG ratings disagreement corresponds to a 1.1% decrease in gross trading volume.

To mitigate concerns about potential omitted variable bias, specifically that ESG disclosure quality or transparency may jointly influence both ESG ratings disagreement and trading behaviour, we include Bloomberg's ESG disclosure score as a control variable in our regression models. This score captures the breadth and quality of ESG-related information disclosed by firms through, inter alia, sustainability reports, annual reports, and corporate websites. Scores range from 0.1 to 100, with higher values indicating more comprehensive and transparent ESG reporting (Christensen et al. 2022). Supporting Information S1: Table SOA4 in the Online Appendix presents the results from an extended model that includes ESG disclosure scores as an additional control variable. Across all specifications, our main finding remains robust: the standardised ESG ratings disagreement measure (STD_ESG_DISG) continues to exhibit a highly statistically significant negative association with abnormal trading volume. This suggests that the observed relationship is not driven by differences in firms' ESG disclosure practices. Overall, these findings help alleviate concerns about omitted variable bias related to disclosure quality.

As noted in Section 3.1.2, our final measure of ESG ratings disagreement is calculated as the average of the pairwise standard deviations of the percentile ranks assigned by the three agencies for each firm-month. To address concerns regarding potential selection bias, particularly the exclusion of less visible or less frequently rated firms, we conduct a robustness test using an expanded sample that includes firms with ESG ratings from at least two agencies, rather than restricting the analysis to those rated by all three. While the number of observations increases substantially, thereby enhancing the representativeness of our dataset, our key results remain robust. Regressions reported in Supporting Information S1: Table SOA5 in the Online Appendix show that the standardised measure of ESG rating disagreement continues to be negatively associated with abnormal trading volume. This provides reassurance that our findings are not driven by the initial restriction to firms with coverage from all three ESG ratings providers.[9]

4.2 | Reverse Causality

A potential source of concern in our analyses is reverse causality, whereby low trading volume, especially for less liquid or less scrutinised firms, may itself contribute to greater ESG ratings disagreement, due to weaker price signals (O'Hara 2003) and greater information asymmetries (Holod and Peek 2007). To explore this possibility, we assess whether past trading volumes predict subsequent ESG disagreement. More specifically, we split the sample at the median of AbLogTurnover and AbMaLogTurnover and examine the predictive power of lagged trading volume, both below and above the median, on ESG disagreement.

The results of this sample-split analysis are reported in Table 4. Unlike the conjecture above, we observe that across both subsamples (below- and above-median turnover), lagged trading volume does not significantly predict subsequent ESG rating disagreement; that is, volume at time t–1 does not predict disagreement at time t. In fact, the coefficients on $\text{AbLogTurnover}_{i,t-1}$ and $\text{AbMaLogTurnover}_{i,t-1}$ are small and statistically insignificant in all specifications. These findings provide empirical support against concerns of reverse causality and reinforce the directionality of our interpretation; namely, that ESG disagreement influences trading behaviour rather than being driven by it.

4.3 | Temporal Dynamics of ESG Ratings Disagreement and Market Reaction

We now investigate how the relationship between ESG ratings disagreement and trading volume may have evolved over time. The period covered by our sample coincides with significant structural developments in the ESG disclosure landscape and rating industry practices, which could plausibly influence both the extent of disagreement between rating agencies and the interpretation of it by market participants.

Specifically, several major milestones occurred between 2016 and 2018 that are likely to have enhanced the availability, standardisation, and visibility of ESG information. These include the release of sector-specific disclosure standards by the Sustainability Accounting Standards Board (SASB) in 2016 (SASB 2016); the updates to the GRI standards in 2016 (GRI 2022); the release of recommendations by the Task Force on Climate-Related Financial Disclosures (TCFD) in 2017 (TCFD 2017); and, importantly, a notable change in methodology implemented by Sustainalytics in 2018 (Rzeźnik et al. 2022).

Given the clustering of these developments, we split the sample at 2017 (inclusive), enabling us to compare results from an earlier phase of ESG development (2009–2016) to a later phase marked by heightened ESG attention and evolving rating practices (2017–2022). This approach allows us to examine whether the market response to ESG ratings disagreement has changed over time, potentially reflecting shifts in disclosure practices, investor awareness, and the methodologies employed by rating agencies.

Table 5 reports the results of this test. In the earlier period (2009–2016), we find no significant relationship between ESG ratings disagreement and trading volume. However, in the later part of the sample (2017–2022), the coefficients on disagreement are negative and highly significant across both specifications. These findings suggest that ESG ratings disagreement has become more salient to investors over time, consistent with the findings of Christensen et al. (2022).

This pattern is particularly striking given the concurrent improvements in ESG disclosure. One might expect greater transparency to reduce disagreement and its informational value. However, our results point to a different dynamic: despite enhancements in the ESG disclosure landscape, ESG ratings

TABLE 4 | Abnormal trading volume and ESG ratings' disagreement.

	(1) $STD\_ESG\_DISG_{i,t}$	(2) $STD\_ESG\_DISG_{i,t}$	(3) $STD\_ESG\_DISG_{i,t}$	(4) $STD\_ESG\_DISG_{i,t}$
$AbLogTurnover_{i,t-1}$	−0.017	0.004		
	(−1.092)	(0.289)		
$AbMaLogTurnover_{i,t-1}$			−0.026	−0.022
			(−1.579)	(−1.605)
SIZE	0.246***	0.238***	0.237***	0.253***
	(4.719)	(4.766)	(4.448)	(5.207)
ROA	−0.461	−0.700*	−0.594	−0.603
	(−1.134)	(−1.813)	(−1.505)	(−1.529)
MTB	−0.005*	−0.005**	−0.006**	−0.004
	(−1.769)	(−2.031)	(−2.342)	(−1.326)
LEV	0.906***	0.758***	0.986***	0.671***
	(4.728)	(4.283)	(5.250)	(3.733)
ANALYSTS	−0.012**	−0.015***	−0.011**	−0.015***
	(−2.390)	(−3.123)	(−2.275)	(−3.101)
INST_OWNERSHIP	−0.003	−0.001	−0.002	−0.002
	(−1.075)	(−0.550)	(−0.814)	(−0.849)
VOLATILITY	4.044***	3.590***	5.442***	2.305***
	(4.445)	(7.571)	(8.328)	(4.404)
SPREAD	26.076***	15.038*	26.019***	8.839
	(3.286)	(1.910)	(3.701)	(1.006)
Log(DISP)	0.033***	0.037***	0.030***	0.041***
	(3.066)	(3.869)	(3.067)	(4.056)
Firm fixed effects	Yes	Yes	Yes	Yes
Month fixed effects	Yes	Yes	Yes	Yes
SE clustered by firm	Yes	Yes	Yes	Yes
Sample	Below median	Above median	Below median	Above median
R-squared	0.053	0.052	0.060	0.044
Firm-months (*N*)	29,750	29,749	29,749	29,750
Number of firms	1277	1274	1278	1274

Note: This table reports the results of the relationship between two measures of abnormal trading volume, namely abnormal log turnover [Columns (1) and (2)] and abnormal market-adjusted log turnover [Columns (3) and (4)], and ESG ratings' disagreement. $AbLogTurnover_{i,t-1}$ (Abnormal log turnover) is computed according to Equation (1). $AbMaLogTurnover_{i,t-1}$ (Abnormal market-adjusted log turnover) is computed according to Equation (3). $STD\_ESG\_DISG_{i,t}$ (ESG ratings' disagreement) is the average of the pairwise standard deviations (standardised to have 0 mean and 1 standard deviation) between the percentile ranks of monthly ESG scores provided to each firm by the three ESG rating providers: MSCI-IVA, LSEG-ESG, and Sustainalytics. The sample used in Column 1 (2) includes observations with below- (above-) median values of AbLogTurnover. The sample used in Column 3 (4) includes observations with below- (above-) median values of AbMaLogTurnover. Control variables are described in Table A1 in the Appendix A. All variables are winsorized at the 1% and 99% levels. Intercept included but not reported. All models include firm and month fixed effects. Standard errors are clustered by firm, and the resultant *t*-statistics are shown in parentheses. Significance level at 10%, 5%, or 1% is indicated by *, **, or ***, respectively.

disagreement appears to have become more meaningful and market-relevant after 2016. This may be due to investors becoming more accustomed to ESG data quality and recognising that disagreement among agencies reflects real ambiguity or complexity in underlying ESG performance. Additionally, increased transparency may have made disagreements more visible, allowing investors to respond to them more systematically.

Overall, these temporal dynamics underscore the importance of contextualising ESG ratings disagreement within the broader regulatory and institutional environment. The observed shift in investor response reinforces the idea that disagreement is not simply noise but can convey information that investors incorporate into their trading behaviour, especially when the ESG ecosystem is sufficiently developed to support such interpretation.

4.4 | ESG Ratings' Disagreement and Information Uncertainty

To further test the uncertainty-based explanation of our main results, we use analysts' EPS forecast dispersion as a proxy for

TABLE 5 | ESG ratings' disagreement and abnormal trading volume (sub-samples).

	(1) $\text{AbLogTurnover}_{i,t}$	(2) $\text{AbMaLogTurnover}_{i,t}$	(3) $\text{AbLogTurnover}_{i,t}$	(4) $\text{AbMaLogTurnover}_{i,t}$
$\text{STD\_ESG\_DISG}_{i,t}$	−0.002	−0.002	−0.017***	−0.015***
	(−0.699)	(−0.766)	(−6.324)	(−6.311)
$\text{AbLogTurnover}_{i,t-1}$	0.402***		0.430***	
	(48.876)		(84.963)	
$\text{AbMaLogTurnover}_{i,t-1}$		0.420***		0.476***
		(44.714)		(88.139)
SIZE	0.100***	0.054***	−0.056***	−0.035***
	(5.346)	(3.531)	(−6.305)	(−4.454)
ROA	0.288	0.195	0.195**	0.083
	(1.578)	(1.310)	(2.065)	(0.944)
MTB	0.002**	0.000	0.001	0.001**
	(2.119)	(0.277)	(1.311)	(2.291)
LEV	−0.298***	−0.229***	−0.225***	−0.193***
	(−5.073)	(−4.778)	(−7.806)	(−7.350)
ANALYSTS	0.001	−0.000	0.001	0.001
	(0.697)	(−0.065)	(1.174)	(1.432)
INST_OWNERSHIP	0.000	0.001	0.002***	0.001*
	(0.105)	(1.354)	(3.528)	(1.914)
VOLATILITY	18.935***	13.685***	12.249***	8.384***
	(34.978)	(29.300)	(74.848)	(45.171)
SPREAD	−46.662***	−34.316***	−21.001***	−25.959***
	(−4.347)	(−3.990)	(−9.994)	(−12.441)
Log(DISP)	−0.034***	−0.025***	−0.026***	−0.018***
	(−7.671)	(−6.668)	(−13.819)	(−10.107)
Firm fixed effects	Yes	Yes	Yes	Yes
Month fixed effects	Yes	Yes	Yes	Yes
SE clustered by firm	Yes	Yes	Yes	Yes
Sample period	2009–2016	2009–2016	2017–2022	2017–2022
R-squared	0.431	0.328	0.454	0.328
Firm-months (*N*)	13,110	13,110	46,389	46,389
Number of firms	673	673	1294	1294

Note: This table reports the results of the relationship between ESG ratings' disagreement and two measures of abnormal trading volume, namely abnormal log turnover [Columns (1) and (3)] and abnormal market-adjusted log turnover [Columns (2) and (4)]. $\text{AbLogTurnover}_{i,t}$ (Abnormal log turnover) is computed according to Equation (1). $\text{AbMaLogTurnover}_{i,t}$ (Abnormal market-adjusted log turnover) is computed according to Equation (3). $\text{STD\_ESG\_DISG}_{i,t}$ (ESG ratings' disagreement) is the average of the pairwise standard deviations (standardised to have 0 mean and 1 standard deviation) between the percentile ranks of monthly ESG scores provided to each firm by the three ESG rating providers: MSCI-IVA, LSEG-ESG, and Sustainalytics. Control variables are described in Table A1 in the Appendix A. All variables are winsorized at the 1% and 99% levels. Intercept included but not reported. Regressions in Columns (1)–(2) are run on the sub-sample 2009–2016, whereas regressions in Columns (3)–(4) are run on the sub-sample 2017–2022. All models include firm and month fixed effects. Standard errors are clustered by firm, and the resultant *t*-statistics are shown in parentheses. Significance level at 10%, 5%, or 1% is indicated by *, **, or ***, respectively.

information uncertainty and estimate a panel regression model to examine the prediction that ESG ratings' disagreement creates more information uncertainty in the market. Previous research has used the dispersion among analysts' forecasts as a proxy for information uncertainty (Barron et al. 1998; Choi 2018; Zhang 2006a). The rationale for using analysts forecast dispersion as a proxy for information uncertainty rather than for belief heterogeneity is confirmed empirically by Garfinkel (2009), who shows that differences in investors' private valuations (from limit order data) are not positively associated with dispersion in analysts' forecasts.

To measure analyst forecast dispersion, we obtain the dispersion of analysts' 1-year EPS forecasts from the I/B/E/S database summary statistics. We calculate dispersion as the standard deviation of different EPS forecasts, scaled by the absolute value of the mean forecast for each firm-month:

$$\text{DISP}_{i,t} = \frac{\text{STD.DEV(FORECASTS)}_{i,t}}{|\text{MEAN\_FORCASTS}_{i,t}|}. \tag{5}$$

The panel regression model to examine the prediction that ESG ratings' disagreement creates more information uncertainty in the market is as follows:

$$\begin{aligned}\text{Log(DISP)}_{i,t} = \beta_0 &+ \beta_1 \text{STD\_ESG\_DISG}_{i,t} \\ &+ \beta_2 \text{Log(DISP)}_{i,t-1} + \sum \beta_j \text{Controls} \\ &+ \gamma_1 + \gamma_2 + e_{i,t}.\end{aligned} \tag{6}$$

Here, Log(DISP) represents the natural logarithm of the standard deviation of analysts' 1-year EPS forecasts (scaled by absolute mean forecast) for each firm-month. STD_ESG_DISG represents ESG ratings disagreement, measured as the average of the pairwise standard deviations of the percentile ranks of ESG scores from MSCI-IVA, LSEG-ESG, and Sustainalytics. We standardise ESG ratings disagreement to a mean of zero and a standard deviation of one, following Cookson and Niessner (2020). Standardising ESG rating disagreement lets us interpret it as the percentage change in the analysts forecasts dispersion for each one standard deviation change in ESG ratings' disagreement.

Our focus is on the coefficient β_1 in Equation (6), which examines the association between ESG ratings disagreement and information uncertainty as proxied by analysts' forecast dispersion. Thus, we expect β to be positive for Log(DISP) and the results presented in Table 6 show the coefficient is positive and statistically significant, suggesting that ESG ratings' disagreements generate more information uncertainty. Economically, a one standard deviation increase in ESG ratings disagreement links to a 1.8% increase in forecast dispersion. The result is consistent with our baseline results and prior empirical literature (Kimbrough et al. 2024).

TABLE 6 | ESG ratings' disagreement and information uncertainty.

	(1) $\text{Log(DISP)}_{i,t}$
$\text{STD\_ESG\_DISG}_{i,t}$	0.018***
	(3.937)
$\text{Log(DISP)}_{i,t-1}$	0.690***
	(129.975)
SIZE	−0.042***
	(−3.395)
ROA	−1.444***
	(−7.316)
MTB	−0.003***
	(−5.045)
LEV	0.391***
	(8.266)
ANALYSTS	0.004***
	(3.980)
ERRORS	0.058***
	(22.456)
INST_OWNERSHIP	−0.001*
	(−1.828)
Firm fixed effects	Yes
Month fixed effects	Yes
SE clustered by firm	Yes
R-squared	0.592
Firm-months (N)	57,258
Number of firms	1297

Note: This table reports the results of the relationship between ESG ratings' disagreement and information uncertainty. Information uncertainty is proxied using analysts forecasts dispersion for firm i in month t (Log(DISP)). Log(DISP) is the natural logarithm of the standard deviation of 1-year EPS forecasts scaled by the absolute value of the mean forecasts for firm i in month t. $\text{STD\_ESG\_DISG}_{i,t}$ (ESG ratings' disagreement) is the average of the pairwise standard deviations (standardised to have 0 mean and 1 standard deviation) between the percentile ranks of monthly ESG scores provided to each firm by the three ESG rating providers: MSCI-IVA, LSEG-ESG, and Sustainalytics. ERRORS (analyst EPS forecast errors) is the natural logarithm of the absolute difference between the mean 1-year EPS forecast and its actual value scaled by the absolute value of the mean forecast for firm i in month t–1. The remaining control variables are described in Table A1 in the Appendix A. All variables are winsorized at the 1% and 99% levels. Intercept included but not reported. All models include firm and month fixed effects. Standard errors are clustered by firm, and the resultant t-statistics are shown in parentheses. Significance level at 10%, 5%, or 1% is indicated by *, **, or ***, respectively.

4.5 | Moderating Role of Analyst Coverage and Market Volatility

To further investigate the conditions under which ESG ratings disagreement exerts a stronger impact on trading activity, we examine two potential sources of variation in investor uncertainty: analyst coverage and market volatility. Prior literature suggests that lower analyst coverage and heightened market volatility may both contribute to higher information asymmetry and investor uncertainty (Bali et al. 2018; Frankel and Li 2004), thereby amplifying the effect of disagreement in ESG assessments.

We, therefore, start by splitting the sample based on the median number of analysts following each firm, which in our sample is 11 analysts. Columns (1) and (2) of Table 7 report results for firms with low analyst coverage (≤ 11 analysts), while Columns (3) and (4) report results for high analyst coverage (≥ 12 analysts). The results show that ESG ratings disagreement has a negative and statistically significant effect on abnormal trading volume in the low analyst coverage subsample. Specifically, the coefficients range from −0.026 to −0.022 and are significant at the 1% level. In contrast, the coefficients in the high analyst coverage subsample are smaller in magnitude and statistically insignificant. These findings suggest that the dampening effect of ESG disagreement on trading volume is concentrated among firms with limited analyst attention, consistent with the notion that disagreement is more important when external information is lower.

Next, we explore whether the relationship between ESG ratings disagreement and trading volume is moderated by overall

TABLE 7 | ESG ratings' disagreement and abnormal trading volume (split by number of analysts).

	(1) $AbLogTurnover_{i,t}$	(2) $AbMaLogTurnover_{i,t}$	(3) $AbLogTurnover_{i,t}$	(4) $AbMaLogTurnover_{i,t}$
$STD\_ESG\_DISG_{i,t}$	−0.026***	−0.022***	−0.002	−0.003
	(−7.375)	(−6.988)	(−0.914)	(−1.561)
$AbLogTurnover_{i,t-1}$	0.439***		0.408***	
	(72.876)		(62.778)	
$AbMaLogTurnover_{i,t-1}$		0.483***		0.447***
		(77.087)		(58.544)
SIZE	−0.059***	−0.042***	0.012	0.002
	(−5.823)	(−4.637)	(1.391)	(0.227)
ROA	0.043	−0.074	0.465***	0.327***
	(0.386)	(−0.726)	(4.269)	(3.320)
MTB	0.001	0.001	0.001**	0.001*
	(0.850)	(0.968)	(2.037)	(1.916)
LEV	−0.219***	−0.187***	−0.192***	−0.164***
	(−6.593)	(−6.104)	(−5.747)	(−5.773)
ANALYSTS	−0.003*	−0.003**	0.001	0.001
	(−1.754)	(−2.226)	(1.296)	(1.512)
INST_OWNERSHIP	0.001***	0.001**	0.001	0.000
	(2.650)	(2.024)	(1.432)	(0.805)
VOLATILITY	12.064***	8.659***	14.048***	8.685***
	(59.231)	(36.725)	(59.189)	(35.661)
SPREAD	−19.875***	−24.125***	−46.731***	−51.819***
	(−9.327)	(−11.309)	(−7.215)	(−8.606)
Log(DISP)	−0.021***	−0.014***	−0.038***	−0.022***
	(−8.924)	(−6.396)	(−14.922)	(−10.378)
Firm fixed effects	Yes	Yes	Yes	Yes
Month fixed effects	Yes	Yes	Yes	Yes
SE clustered by firm	Yes	Yes	Yes	Yes
Number of analysts	Up to 11	Up to 11	More than 11	More than 11
R-squared	0.443	0.342	0.447	0.299
Firm-months (N)	30,432	30,432	29,067	29,067
Number of firms	1107	1107	597	597

Note: This table reports the results of the relationship between ESG ratings' disagreement and two measures of abnormal trading volume, namely abnormal log turnover [Columns (1) and (3)] and abnormal market-adjusted log turnover [Columns (2) and (4)]. $AbLogTurnover_{i,t}$ (Abnormal log turnover) is computed according to Equation (1). $AbMaLogTurnover_{i,t}$ (Abnormal market-adjusted log turnover) is computed according to Equation (3). $STD\_ESG\_DISG_{i,t}$ (ESG ratings' disagreement) is the average of the pairwise standard deviations (standardised to have 0 mean and 1 standard deviation) between the percentile ranks of monthly ESG scores provided to each firm by the three ESG rating providers: MSCI-IVA, LSEG-ESG, and Sustainalytics. Columns (1) and (2) report results for firm-month observations with low analyst coverage (≤ 11 analysts), while Columns (3) and (4) report results for firm-month observations with high analyst coverage (≥ 12 analysts). Control variables are described in Table A1 in the Appendix A. All variables are winsorized at the 1% and 99% levels. Intercept included but not reported. All models include firm and month fixed effects. Standard errors are clustered by firm, and the resultant t-statistics are shown in parentheses. Significance level at 10%, 5%, or 1% is indicated by *, **, or ***, respectively.

market conditions, as proxied by VOLATILITY. We split the sample based on the median level of stock volatility and present the results in Table 8. The results show that ESG ratings disagreement has a significantly stronger negative effect on trading activity during high volatility periods (Columns 2 and 4), compared to low volatility periods (Columns 1 and 3). Moreover, unreported Wald tests reveal that the coefficients on STD_ESG_DISG across these volatility regimes (Columns 1 vs. 2) are statistically different. These results support the view that ESG ratings disagreement is more salient during turbulent market periods, when uncertainty and investor sensitivity to conflicting information are heightened.

Together, these moderation analyses reinforce the main findings and suggest that the effect of ESG ratings disagreement on trading activity is not uniform, but instead varies systematically with the level of information asymmetry and market-wide uncertainty.

TABLE 8 | ESG ratings' disagreement and abnormal trading volume (split by median volatility).

	(1) $AbLogTurnover_{i,t}$	(2) $AbLogTurnover_{i,t}$	(3) $AbMaLogTurnover_{i,t}$	(4) $AbMaLogTurnover_{i,t}$
$STD\_ESG\_DISG_{i,t}$	−0.005**	−0.024***	−0.002	−0.024***
	(−2.159)	(−6.136)	(−1.302)	(−6.761)
$AbLogTurnover_{i,t-1}$	0.426***	0.435***		
	(78.830)	(73.234)		
$AbMaLogTurnover_{i,t-1}$			0.444***	0.491***
			(74.878)	(77.913)
SIZE	−0.001	−0.050***	0.004	−0.044***
	(−0.078)	(−4.977)	(0.604)	(−5.278)
ROA	0.149	0.211**	0.185	0.096
	(1.123)	(2.240)	(1.465)	(1.122)
MTB	0.000	0.001	0.000	0.001**
	(1.060)	(1.571)	(0.365)	(2.083)
LEV	−0.103***	−0.237***	−0.133***	−0.184***
	(−3.820)	(−7.334)	(−5.680)	(−6.272)
ANALYSTS	−0.001	0.002**	−0.001	0.002***
	(−0.891)	(2.495)	(−1.644)	(2.647)
INST_OWNERSHIP	−0.000	0.001**	−0.000	0.001
	(−1.016)	(2.504)	(−0.272)	(1.487)
VOLATILITY	20.753***	11.699***	16.427***	8.051***
	(42.303)	(62.666)	(36.481)	(35.919)
SPREAD	−29.543***	−20.170***	−25.683***	−25.855***
	(−8.494)	(−8.639)	(−7.452)	(−11.218)
Log(DISP)	−0.029***	−0.032***	−0.019***	−0.023***
	(−12.134)	(−14.126)	(−8.934)	(−10.967)
Firm fixed effects	Yes	Yes	Yes	Yes
Month fixed effects	Yes	Yes	Yes	Yes
SE clustered by Firm	Yes	Yes	Yes	Yes
Volatility	Low	High	Low	High
R-squared	0.309	0.455	0.271	0.344
Firm-months (*N*)	29,750	29,749	29,750	29,749
Number of firms	997	1282	997	1282

Note: This table reports the results of the relationship between ESG ratings' disagreement and two measures of abnormal trading volume, namely abnormal log turnover [Columns (1) and (2)] and abnormal market-adjusted log turnover [Columns (3) and (4)]. $AbLogTurnover_{i,t}$ (Abnormal log turnover) is computed according to Equation (1). $AbMaLogTurnover_{i,t}$ (Abnormal market-adjusted log turnover) is computed according to Equation (3). $STD\_ESG\_DISG_{i,t}$ (ESG ratings' disagreement) is the average of the pairwise standard deviations (standardised to have 0 mean and 1 standard deviation) between the percentile ranks of monthly ESG scores provided to each firm by the three ESG rating providers: MSCI-IVA, LSEG-ESG, and Sustainalytics. Columns (1) and (3) report results for firm-month observations with low volatility, while Columns (2) and (4) report results for firm-month observations with high volatility. Control variables are described in Table A1 in the Appendix A. All variables are winsorized at the 1% and 99% levels. Intercept included but not reported. All models include firm and month fixed effects. Standard errors are clustered by firm, and the resultant *t*-statistics are shown in parentheses. Significance level at 10%, 5% or 1% is indicated by *, **, or ***, respectively.

4.6 | Cross Sectional Analysis: High Versus Low ESG Performance

In this section, we examine whether the relationship between ESG ratings disagreement and trading volume varies when the scope of disagreement is about high versus low ESG performance. Prior research shows that informed trading increases for above-average signals leading to a crowding in effect (Schneemeier 2023). Therefore, we predict that disagreement about high ESG performance signal will result in more trading as investors crowd in. In contrast, our expectation for disagreement about low ESG performance is less trading as investors crowd out. To test these predictions, we split our sample into two groups based on the median value of average ESG performance and rerun our baseline model for each group as well as for the subsample of firms at the top quartile of average ESG performance.

Table 9 presents the results which indicate that, for the low ESG performance group, the negative impact on trading stays statistically significant at the 1% level and increases in economic magnitude. For the high ESG performance group, the impact is neither statistically nor economically significant. For the top quartile ESG performance, the relationship between ESG ratings disagreement and abnormal trading turns positive and is statistically significant.

4.7 | Institutional Heterogeneity: Norm-Constrained and Activist Investors

Our baseline results show that institutional ownership in general has no significant impact on abnormal trading volume. Given the heterogeneity among institutional investors in their ESG investment objectives, we perform further analysis examining the cross-sectional variation in the trading volume response by different subgroups of institutional investors. Avramov et al. (2022) shows that ESG ratings' disagreement matters more to ESG-sensitive institutional

TABLE 9 | Trading volume response: High versus low ESG performance.

	(1) Low ESG performance	(2) High ESG performance	(3) Top quartile ESG performance
$STD\_ESG\_DISG_{i,t}$	−0.020***	−0.000	0.009**
	(−4.727)	(−0.092)	(2.369)
$AbLogTurnover_{i,t-1}$	0.423***	0.420***	0.420***
	(70.825)	(64.386)	(44.271)
SIZE	−0.023**	−0.005	0.024*
	(−2.000)	(−0.487)	(1.850)
ROA	0.126	0.260*	0.561***
	(1.147)	(1.740)	(2.661)
MTB	0.001	0.001***	0.001*
	(0.980)	(2.686)	(1.886)
LEV	−0.158***	−0.260***	−0.235***
	(−4.360)	(−6.719)	(−4.649)
ANALYSTS	0.001	0.000	−0.000
	(1.427)	(0.219)	(−0.412)
INST_OWNERSHIP	0.000	0.001	0.000
	(0.776)	(1.367)	(0.333)
VOLATILITY	13.820***	12.422***	12.242***
	(59.255)	(57.104)	(41.389)
SPREAD	−25.054***	−22.836***	−31.690***
	(−9.408)	(−6.051)	(−6.540)
Log(DISP)	−0.026***	−0.032***	−0.031***
	(−9.895)	(−12.833)	(−9.938)
Firm fixed effects	Yes	Yes	Yes
Month fixed effects	Yes	Yes	Yes
SE clustered by firm	Yes	Yes	Yes
R-squared	0.421	0.464	0.490
Firm-months (N)	29,750	29,749	14,867
Number of firms	1091	987	641

Note: This table reports the results of the relationship between ESG ratings' disagreement and abnormal trading volume. The sample is split along the median value of average ESG performance. Firm-month observations are considered as "low ESG performance" if their value is equal to or below the median (Column 1), and "high ESG performance" if their value is above the median (Column 2). Column (3) presents results for subsample of firm-month observations in the top quartile ESG performance. Firm-level average ESG performance is obtained by computing the pairwise average ESG scores and then calculating the average across all rater-pairs. The dependent variable is AbLogTurnover (Abnormal log turnover), which is computed according to Equation (1). $STD\_ESG\_DISG_{i,t}$ (ESG ratings' disagreement) is the average of the pairwise standard deviations (standardised to have 0 mean and 1 standard deviation) between the percentile ranks of monthly ESG scores provided to each firm by the three ESG rating providers: MSCI-IVA, LSEG-ESG, and Sustainalytics. Control variables are described in Table A1 in the Appendix A. All variables are winsorized at the 1% and 99% levels. Intercept included but not reported. All models include firm and month fixed effects. Standard errors are clustered by firm, and the resultant t-statistics are shown in parentheses. Significance level at 10%, 5%, or 1% is indicated by *, **, or ***, respectively.

TABLE 10 | Trading volume response: ESG-sensitive institutional investors.

	(1) $AbLogTurnover_{i,t}$	(2) $AbMaLogTurnover_{i,t}$
NORM	−0.006	−0.009**
	(−1.142)	(−2.097)
$STD\_ESG\_DISG_{i,t}$	−0.010***	−0.010***
	(−2.734)	(−3.046)
$STD\_ESG\_DISG_{i,t}$ × NORM	−0.010***	−0.007**
	(−2.704)	(−2.296)
NON-NORM	0.006*	0.005
	(1.736)	(1.475)
$STD\_ESG\_DISG_{i,t}$ × NON-NORM	0.003	0.004
	(1.070)	(1.263)
$AbLogTurnover_{i,t-1}$	0.428***	
	(98.054)	
$AbMaLogTurnover_{i,t-1}$		0.470***
		(98.842)
SIZE	−0.017**	−0.015***
	(−2.372)	(−2.664)
ROA	0.145*	0.039
	(1.791)	(0.541)
MTB	0.001***	0.001**
	(2.606)	(2.410)
LEV	−0.197***	−0.164***
	(−8.339)	(−8.094)
ANALYSTS	0.001	0.000
	(1.146)	(1.067)
INST_OWNERSHIP	0.001*	0.001
	(1.738)	(1.478)
VOLATILITY	12.498***	8.326***
	(80.021)	(50.756)
SPREAD	−24.598***	−29.966***
	(−10.164)	(−13.181)
Log(DISP)	−0.030***	−0.019***
	(−16.660)	(−12.004)
Firm fixed effects	Yes	Yes
Month fixed effects	Yes	Yes
SE clustered by firm	Yes	Yes
R-squared	0.433	0.317
Firm-months (*N*)	59,499	59,499
Number of firms	1303	1303

Note: This table reports the results of regressions examining the role of ESG-sensitive institutional investors in explaining the relationship between ESG ratings' disagreement and two measures for abnormal trading volume, namely abnormal log turnover [Column (1)] and abnormal market-adjusted log turnover [Column (2)]. $AbLogTurnover_{i,t}$ (Abnormal log turnover) is computed according to Equation (1). $AbMaLogTurnover_{i,t}$ (Abnormal market-adjusted log turnover) is computed according to Equation (3). ESG-sensetive investors are defined as those constrained by social norms. NORM is a dummy variable that equals one if ownership by norm-constrained institutions (13F type codes 1, 2, and 5) is greater than the sample mean ownership by such institutions, and zero otherwise. NON-NORM is a dummy variable that equals one if ownership by non-norm-constrained institutions (13F type codes 3 and 4) is greater than the sample mean ownership by such institutions, and zero otherwise. $STD\_ESG\_DISG_{i,t}$ (ESG ratings' disagreement) is the average of the pairwise standard deviations (standardised to have 0 mean and 1 standard deviation) between the percentile ranks of monthly ESG scores provided to each firm by the three ESG rating providers: MSCI-IVA, LSEG-ESG, and Sustainalytics. Control variables are described in Table A1 in the Appendix A. All variables are winsorized at the 1% and 99% levels. Intercept included but not reported. All models include firm and month fixed effects. Standard errors are clustered by firm, and the resultant *t*-statistics are shown in parentheses. Significance level at 10%, 5%, or 1% is indicated by *, **, or ***, respectively.

TABLE 11 | Trading volume response: Activist investors.

	(1) $\mathbf{AbLogTurnover}_{i,t}$	(2) $\mathbf{AbMaLogTurnover}_{i,t}$
ACTIVIST INVESTORS	0.087***	0.086***
	(8.255)	(8.245)
$STD\_ESG\_DISG_{i,t}$	−0.013***	−0.012***
	(−6.197)	(−6.339)
$STD\_ESG\_DISG_{i,t}$ × ACTIVIST INVESTORS	−0.007	−0.009
	(−0.669)	(−0.854)
$AbLogTurnover_{i,t-1}$	0.426***	
	(97.602)	
$AbMaLogTurnover_{i,t-1}$		0.469***
		(98.504)
SIZE	−0.019***	−0.018***
	(−2.740)	(−3.166)
ROA	0.151*	0.046
	(1.862)	(0.634)
MTB	0.001***	0.001**
	(2.599)	(2.375)
LEV	−0.199***	−0.166***
	(−8.406)	(−8.208)
ANALYSTS	0.001	0.001
	(1.390)	(1.373)
INST_OWNERSHIP	0.001*	0.000
	(1.771)	(1.178)
VOLATILITY	12.453***	8.279***
	(80.315)	(50.739)
SPREAD	−24.698***	−30.092***
	(−10.161)	(−13.212)
Log(DISP)	−0.030***	−0.019***
	(−16.892)	(−12.234)
Firm fixed effects	Yes	Yes
Month fixed effects	Yes	Yes
SE clustered by firm	Yes	Yes
R-squared	0.434	0.318
Firm-months (*N*)	59,499	59,499
Number of firms	1303	1303

Note: This table reports the results of the relationship between ESG ratings' disagreement and two measures of abnormal trading volume, namely abnormal log turnover [Column (1)] and abnormal market-adjusted log turnover [Column (2)]. $AbLogTurnover_{i,t}$ (Abnormal log turnover) is computed according to Equation (1). $AbMaLogTurnover_{i,t}$ (Abnormal market-adjusted log turnover) is computed according to Equation (3). $STD\_ESG\_DISG_{i,t}$ (ESG ratings' disagreement) is the average of the pairwise standard deviations (standardised to have 0 mean and 1 standard deviation) between the percentile ranks of monthly ESG scores provided to each firm by the three ESG rating providers: MSCI-IVA, LSEG-ESG, and Sustainalytics. ACTIVIST INVESTOR is a dummy variable equal to 1 for firm-month observations in which the firm is subject to shareholder activism, as identified through Schedule 13D filings in the Audit Analytics database, and 0 otherwise. The remaining control variables are described in Table A1 in the Appendix A. All variables are winsorized at the 1% and 99% levels. Intercept included but not reported. All models include firm and month fixed effects. Standard errors are clustered by firm, and the resultant *t*-statistics are shown in parentheses. Significance level at 10%, 5%, or 1% is indicated by *, **, or ***, respectively.

investors. Therefore, we expect that the trading volume response from ESG-sensitive investors will be higher. We define ESG-sensitive investors following Hong and Kacperczyk (2009) and Avramov et al. (2022) as institutions that are constrained by social norms (e.g., pension funds, banks, insurance companies, and university endowments). While other institutions including mutual and hedge funds are less constrained by social norms as they are considered to be natural arbitrageurs (Hong and Kacperczyk 2009). We follow their categorisation of institutional investors with 13F type codes 1, 2, and 5 as norm-constrained and institutions with type codes 3 and 4 as those not being constrained by norms.

We first calculate, for each firm, the percentage of shares held by norm-constrained and non-norm-constrained institutional investors. Then, we create two dummy variables: NORM and NON-NORM. NORM equals 1 if a firm's ownership by norm-constrained institutions is above the sample mean, and 0 otherwise. Similarly, NON-NORM equals 1 if a firm's ownership by non-norm-constrained institutions exceeds the sample mean, and 0 otherwise. We then interact both dummies with ESG ratings' disagreement to capture the impact of disagreement on trading volume for each of the two subgroups.

Table 10 presents the results. We find negative and statistically significant coefficients on the interaction term between ESG disagreement and norm-constrained institutions. This indicates that the negative ESG disagreement-trading volume relation is stronger among firms with high ownership by norm-constrained institutions. For firms with above-average ownership by institutions that are not constrained by norms, the interaction term with ESG disagreement is positive but statistically insignificant. Therefore, the results suggest that the impact of ESG ratings' disagreement on abnormal trading is mainly driven by the reaction of norm-constrained institutional investors being more ESG-sensitive.

To further explore institutional heterogeneity, we complement our analysis by focusing on activist investors, which is an influential and information-sensitive class of institutional investors increasingly engaged on ESG matters. Activism events are identified using the Audit Analytics database, which tracks disclosures made in Schedule 13D filings as required under Rule 13d-1(a) of the 1934 Securities Exchange Act. These filings are mandated when an investor acquires more than 5% of a company's voting shares with the intention to influence management, and must be filed within 10 days of reaching the threshold. Based on these filings, we construct an ACTIVIST INVESTOR dummy, which is equal to 1 for firm-months during which a firm is subject to shareholder activism, and 0 otherwise.

Table 11 reports the results from interacting our ESG disagreement measure with the ACTIVIST INVESTOR dummy. We find that activism is associated with significantly higher abnormal trading volume, consistent with the increased activity of activist investors. However, the interaction term between ESG disagreement and activist investors is statistically insignificant, suggesting that trading behaviour among activist investors is not particularly more sensitive to ESG ratings disagreement than that of other investors.

Overall, these analyses underscore the importance of accounting for investor heterogeneity. The sensitivity to ESG ratings disagreement is concentrated among norm-constrained institutions (i.e., those more likely to internalise ESG considerations), whereas activist investors do not appear to respond differentially to ESG rating disagreement.

TABLE 12 | ESG ratings' disagreement and bid-ask spread.

	(1) Spread	(2) Spread
$STD\_ESG\_DISG_{i,t}$	0.003***	0.003***
	(2.788)	(2.713)
$AbLogTurnover_{i,t}$	−0.023***	
	(−10.030)	
$AbLogTurnover_{i,t-1}$	0.002	
	(1.332)	
$AbMaLogTurnover_{i,t}$		−0.027***
		(−12.695)
$AbMaLogTurnover_{i,t-1}$		0.003*
		(1.786)
SIZE	−0.012***	−0.012***
	(−2.684)	(−2.699)
ROA	−0.251***	−0.252***
	(−4.446)	(−4.476)
MTB	−0.001***	−0.001***
	(−4.201)	(−4.156)
LEV	0.044***	0.043***
	(2.832)	(2.816)
ANALYSTS	−0.001**	−0.001**
	(−2.432)	(−2.432)
INST_OWNERSHIP	−0.002***	−0.002***
	(−6.156)	(−6.186)
VOLATILITY	1.153***	1.068***
	(14.760)	(15.468)
Log(DISP)	0.004***	0.004***
	(3.753)	(3.862)
Firm fixed effects	Yes	Yes
Month fixed effects	Yes	Yes
SE clustered by firm	Yes	Yes
R-squared	0.058	0.061
Firm-months (N)	59,499	59,499
Number of firms	1303	1303

Note: This table reports the results of the relationship between ESG ratings' disagreement and Spread. Spread is the relative bid-ask spread for firm i in month t measured as (ask-bid)/((ask+bid)/2). $STD\_ESG\_DISG_{i,t}$ (ESG ratings' disagreement) is the average of the pairwise standard deviations (standardised to have 0 mean and 1 standard deviation) between the percentile ranks of monthly ESG scores provided to each firm by the three ESG rating providers: MSCI-IVA, LSEG-ESG, and Sustainalytics. Regressors in Column (1) include AbLogTurnover (Abnormal log turnover), which is computed according to Equation (1), while regressors in Column (2) include AbMaLogTurnover (Abnormal market-adjusted log turnover), which is computed according to Equation (3). The other control variables are described in Table A1 in the Appendix A. All variables are winsorized at the 1% and 99% levels. Intercept included but not reported. All models include firm and month fixed effects. Standard errors are clustered by firm, and the resultant t-statistics are shown in parentheses. Significance level at 10%, 5%, or 1% is indicated by *, **, or ***, respectively.

4.8 | Additional Analysis

In addition to examining trading volume, we explore the implications of ESG ratings disagreement for market efficiency, particularly through the lens of information asymmetry. A key concern in financial markets is that when investors face conflicting signals, such as diverging ESG ratings across providers, it may become more difficult to assess a firm's true sustainability profile or overall risk (Larcker et al. 2022a), thereby increasing uncertainty (Kimbrough et al. 2024) and reducing pricing efficiency (Serafeim and Yoon 2023). This uncertainty can manifest in higher trading frictions, particularly through a widening of the bid-ask spread, which serves as a standard proxy for information asymmetry and liquidity cost (Garfinkel 2009).

To investigate this channel, we re-estimate our baseline regression framework using the bid-ask spread (SPREAD in our analyses) as the dependent variable. Table 12 presents the results. In both specifications, we find that the coefficient on STD_ESG_DISG is positive and statistically significant at the 1% level. These results indicate that firms with higher ESG ratings disagreement tend to experience wider bid-ask spreads, consistent with prior empirical findings (Kimbrough et al. 2024) and the interpretation that such disagreement contributes to greater information asymmetry in financial markets.

This finding suggests that ESG disagreement imposes costs not only by potentially discouraging trading activity (as documented earlier) but also by increasing trading costs for those who do engage in transactions. Taken together, these results complement our main analysis and highlight that ESG ratings disagreement may undermine not only market participation but also market efficiency more broadly, through the pricing of informational frictions.

5 | Conclusions

Prior research shows that disagreement among ESG ratings' agencies is associated with uncertainty and/or market disagreement. We test two competing hypotheses: The first is that ESG ratings' disagreement is associated with less trading volume as it leads to more uncertainty in the market. The second hypothesis is that ESG ratings' disagreement is associated with more trading volume due to divergence in investors' beliefs.

In contrast to the positive disagreement–trading relationship documented in other settings in the literature, we find that ESG ratings' disagreement is negatively associated with abnormal (excess) trading. A one standard deviation increase in disagreement corresponds to a 1.3% decline in abnormal trading volume. This result is robust to other measures of trading activity and various testing procedures. Our results also reveal that the disagreement–trading relationship has become more salient over time. While no significant effect is observed during the earlier period of our sample (2009–2016), the negative relationship becomes statistically significant in the later period (2017–2022), coinciding with growing investor attention to ESG issues. Furthermore, ESG ratings disagreement is positively associated with analyst forecast dispersion, supporting the interpretation that disagreement contributes to higher information uncertainty.

We also find that this negative trading response varies across settings. The effect is more pronounced for firms with low analyst coverage and during periods of high market volatility. Furthermore, the relation is stronger for firms with low ESG performance and is mitigated, or even reversed, for firms in the top ESG performance quartile. Finally, our cross-sectional analysis reveals that norm-constrained institutional investors drive the observed negative effect, while activist investors appear unresponsive. We also find that higher ESG ratings disagreement is associated with wider bid-ask spreads, suggesting increased transaction costs and reduced information efficiency.

Overall, the findings presented here demonstrate that trading volume is a critical and previously overlooked facet of market response to ESG information ambiguity, one that captures the tension between uncertainty and disagreement more directly than price-based measures. Empirically, we are, to our knowledge, the first to show robust evidence that ESG ratings disagreement influences trading volume in equity markets. In doing so, we bridge a gap between the sustainable finance literature and the classic finance literature on differences of opinion and trading activity. By highlighting volume effects, our study complements prior work on return and risk implications of ESG divergence and offers a more comprehensive view of how ESG information frictions translate into market behaviour.

Our findings carry important practical implications for investors and policy-makers. For institutional investors and asset managers, understanding the impact of ESG ratings disagreement can inform portfolio strategy and risk management. Greater standardisation of ESG ratings could play a critical role in mitigating the uncertainty-driven reduction in trading documented in our study. Discrepancies between ESG ratings create ambiguity for investors, leading to disengagement from trading activities due to the inability to confidently assess firms' sustainability profiles. By harmonising methodologies, definitions, and disclosure requirements across ESG rating providers, standardisation would reduce the noise and inconsistency in ESG assessments. This would allow investors to form more consistent and reliable expectations about firms' ESG risks and opportunities, thereby alleviating ambiguity aversion and encouraging greater market participation. Reducing informational frictions would not only support liquidity but also lower transaction costs associated with due diligence efforts needed to reconcile conflicting ESG signals.

In turn, a more standardised ESG rating system would contribute to improved market efficiency. Clearer and more comparable ESG assessments would enhance price discovery by enabling investors to incorporate ESG-related risks and opportunities more systematically into asset valuations. Standardisation would also diminish the adverse selection problems that arise when only better-informed investors are willing to trade, thereby tightening bid-ask spreads and enhancing informational efficiency. Ultimately, by stabilising trading volumes and improving the integration of ESG considerations into investment processes, ESG rating standardisation would strengthen the alignment between capital markets and broader sustainability goals, highlighting the crucial policy implications of our findings. Overall, our findings underscore the importance of addressing ESG ratings disagreement to promote well-functioning financial markets.

Acknowledgements

We are grateful to the editor and two anonymous reviewers for their very helpful comments. We are also thankful to participants at the LUBS Doctoral Conference (Leeds, UK, June 2024) for insightful feedback. Furthermore, Mohammed Quotb gratefully acknowledges financial support from The Egyptian Ministry of Higher Education and Scientific Research represented by The Egyptian Bureau for Cultural and Educational Affairs in London.

Conflicts of Interest

The authors declare no conflicts of interest.

Data Availability Statement

Data subject to third-party restrictions. Restrictions apply to the availability of these data, which were used under license for this study.

Endnotes

[1] This classification is developed through collaboration between Global Sustainable Investment Alliance (GSIA), Principles for Responsible Investment (PRI), CFA Institute, and other leading finance organisations.

[2] Global Sustainable Investment Alliance et al. (2024) provides a comprehensive description on how ESG ratings can be incorporated with other ESG investing strategies: screening, thematic investing, impact investing, and stewardship.

[3] See, for instance, Section 36(c) on page 52 of the BlackRock Investment Funds Prospectus dated 2nd April 2025, which references the use of third-party ESG ratings, specifically MSCI (https://www.blackrock.com/uk/literature/prospectus/blackrock-investment-funds-prospectus.pdf).

[4] To address potential sample selection concerns, we conduct a robustness test by expanding the sample to include firms rated by at least two agencies, rather than restricting it to those rated by all three. The results, which are discussed later in the paper in Section 4.1 and reported in Table OA5 of the Online Appendix, remain consistent.

[5] We exclude firms with a negative market to book ratio because of a high probability of financial distress.

[6] Our sample includes both active and delisted firms (i.e., we do not remove companies that were delisted during our observation period). Firms are followed until delisting or the end of the sample period, whichever comes first. This ensures that our findings are not biased toward surviving firms and provide a more accurate picture of the trading dynamics associated with ESG rating disagreement.

[7] It is plausible that investor responses may not follow a strictly linear pattern. For instance, lower disagreement may be disregarded, while extreme disagreement could trigger more substantial shifts in trading behaviour. Hence, as a robustness check, we test for potential nonlinear effects in the relationship between ESG ratings disagreement and trading volume by including a quadratic term for the standardised measure of ESG disagreement in our baseline regressions. As shown in Supporting Information S1: Table SOA1 in the Online Appendix, the coefficient on the squared term is small in magnitude and statistically insignificant across both dependent variables, suggesting that the relationship is effectively linear within our sample.

[8] To account for potential unobserved heterogeneity at the industry level, we re-estimate our baseline model by including industry fixed effects. As shown in Supporting Information S1: Table SOA2 in the Online Appendix, our main findings remain robust: ESG ratings disagreement continues to be negatively and significantly associated with abnormal trading volume.

[9] To further address concerns about whether excluded firms differ systematically in characteristics relevant to trading behaviour, we conducted *t*-tests comparing sampled firms (those with ratings from all three agencies) to non-sampled firms (excluded due to having only two available ESG ratings). Unreported results show that while the differences in means are statistically significant in most cases, they are economically negligible being very close to zero. This suggests that the two groups do not differ meaningfully in terms of characteristics commonly associated with trading behaviour, such as analyst coverage, return volatility, bid-ask spread, and analysts forecasts dispersion. This strengthens our confidence that the exclusion of these firms does not materially bias our results.

References

Acemoglu, D., V. Chernozhukov, and M. Yildiz. 2016. "Fragility of Asymptotic Agreement Under Bayesian Learning: Fragility of Asymptotic Agreement." *Theoretical Economics* 11, no. 1: 187–225.

Admati, A. R., and P. Pfleiderer. 1988. "A Theory of Intraday Patterns: Volume and Price Variability." *Review of Financial Studies* 1, no. 1: 3–40.

Ajinkya, B. B., R. K. Atiase, and M. J. Gift. 1991. "Volume of Trading and the Dispersion in Financial Analysts' Earnings Forecasts." *Accounting Review* 66, no. 2: 389–401.

Armstrong, C. S., M. S. Heinle, and I. Luneva. 2024. "Financial Information and Diverging Beliefs." *Review of Accounting Studies* 29, no. 3: 2082–2124.

Atmaz, A., and S. Basak. 2018. "Belief Dispersion in the Stock Market." *Journal of Finance* 73, no. 3: 1225–1279.

Avramov, D., S. Cheng, A. Lioui, and A. Tarelli. 2022. "Sustainable Investing With ESG Rating Uncertainty." *Journal of Financial Economics* 145, no. 2: 642–664.

Bali, T. G., A. Bodnaruk, A. Scherbina, and Y. Tang. 2018. "Unusual News Flow and the Cross Section of Stock Returns." *Management Science* 64, no. 9: 4137–4155.

Bamber, L. S., O. E. Barron, and D. E. Stevens. 2011. "Trading Volume Around Earnings Announcements and Other Financial Reports: Theory, Research Design, Empirical Evidence, and Directions for Future Research." *Contemporary Accounting Research* 28, no. 2: 431–471.

Banerjee, S., and I. Kremer. 2010. "Disagreement and Learning: Dynamic Patterns of Trade." *Journal of Finance* 65, no. 4: 1269–1302.

Barron, O. E., O. Kim, S. C. Lim, and D. E. Stevens. 1998. "Using Analysts' Forecasts to Measure Properties of Analysts' Information Environment." *Accounting Review* 73, no. 4: 421–433.

Barron, O. E., R. A. Schneible, and D. E. Stevens. 2018. "The Changing Behavior of Trading Volume Reactions to Earnings Announcements: Evidence of the Increasing Use of Accounting Earnings News by Investors." *Contemporary Accounting Research* 35, no. 4: 1651–1674.

Barron, O. E., and P. S. Stuerke. 1998. "Dispersion in Analysts' Earnings Forecasts as a Measure of Uncertainty." *Journal of Accounting, Auditing & Finance* 13, no. 3: 245–270.

Bax, K., G. Bonaccolto, and S. Paterlini. 2024. "Spillovers in Europe: The Role of ESG." *Journal of Financial Stability* 72: 101221.

Beaver, W. H. 1968. "The Information Content of Annual Earnings Announcements." *Journal of Accounting Research* 6, no. 2: 67–92.

Berg, F., F. Heeb, and J. F. Kölbel (2022a). The Economic Impact of ESG Ratings. https://doi.org/10.2139/ssrn.4088545.

Berg, F., J. F. Koelbel, A. Pavlova, and R. Rigobon (2022c). ESG Confusion and Stock Returns: Tackling the Problem of Noise. https://www.nber.org/papers/w30562.

Berg, F., J. F. Kölbel, and R. Rigobon. 2022b. "Aggregate Confusion: The Divergence of ESG Ratings." *Review of Finance* 26, no. 6: 1315–1344.

Berg, F., A. W. Lo, R. Rigobon, M. Singh, and R. Zhang. 2023. "Quantifying the Returns of ESG Investing: An Empirical Analysis With Six ESG Metrics." *Journal of Portfolio Management* 50, no. 8: 216–238.

Bewley, T. F. 2002. "Knightian Decision Theory. Part I." *Decisions in Economics and Finance* 25, no. 2: 79–110.

BlackRock. (2024). *Blackrock ESG Integration Statement*. https://www.blackrock.com/corporate/literature/publication/blk-esg-investment-statement-web.pdf.

Booker, A., A. Curtis, and V. J. Richardson. 2023. "Investor Disagreement, Disclosure Processing Costs, and Trading Volume: Evidence From Social Media." *Accounting Review* 98, no. 1: 109–137.

Brock, E., J. Nelson, and A. Brackley (2023). Rate the Rates 2023: ESG Ratings at the Crossroads. https://www.erm.com/insights/rate-the-raters-2023/.

Carlin, B. I., F. A. Longstaff, and K. Matoba. 2014. "Disagreement and Asset Prices." *Journal of Financial Economics* 114, no. 2: 226–238.

De Castro, L. I., and A. Chateauneuf. 2011. "Ambiguity Aversion and Trade." *Economic Theory* 48, no. 2–3: 243–273.

CFA Institute. (2024). *What Is ESG Investing?* https://www.cfainstitute.org/insights/articles/what-is-esg-investing.

Choi, H. M. 2018. "A Tale of Two Uncertainties." *Journal of Banking & Finance* 92: 81–99.

Christensen, D. M., G. Serafeim, and A. Sikochi. 2022. "Why Is Corporate Virtue in the Eye of the Beholder? The Case of ESG Ratings." *Accounting Review* 97, no. 1: 147–175.

Cookson, J. A., V. Fos, and M. Niessner (2022). Does Disagreement Facilitate Informed Trading? https://doi.org/10.2139/ssrn.3765092.

Cookson, J. A., and M. Niessner. 2020. "Why Don't We Agree? Evidence From a Social Network of Investors." *Journal of Finance* 75, no. 1: 173–228.

Cornell, B. 2021. "ESG Preferences, Risk and Return." *European Financial Management* 27, no. 1: 12–19.

Cready, W. M., and D. N. Hurtt. 2002. "Assessing Investor Response to Information Events Using Return and Volume Metrics." *Accounting Review* 77, no. 4: 891–909.

Danisman, G. O., and A. Tarazi. 2024. "ESG Activity and Bank Lending During Financial Crises." *Journal of Financial Stability* 70: 101206.

Demetriades, E., and P. N. Politsidis. 2025. "Bank Lending to Fossil Fuel Firms." *Journal of Financial Stability* 76, Article: 101349.

Dhaliwal, D. S., O. Z. Li, A. Tsang, and Y. G. Yang. 2011. "Voluntary Nonfinancial Disclosure and the Cost of Equity Capital: The Initiation of Corporate Social Responsibility Reporting." *Accounting Review* 86, no. 1: 59–100.

Dhaliwal, D. S., S. Radhakrishnan, A. Tsang, and Y. G. Yang. 2012. "Nonfinancial Disclosure and Analyst Forecast Accuracy: International Evidence on Corporate Social Responsibility Disclosure." *Accounting Review* 87, no. 3: 723–759.

Diether, K. B., C. J. Malloy, and A. Scherbina. 2002. "Differences of Opinion and the Cross Section of Stock Returns." *Journal of Finance* 57, no. 5: 2113–2141.

Easley, D., and M. O'Hara. 2009. "Ambiguity and Nonparticipation: The Role of Regulation." *Review of Financial Studies* 22, no. 5: 1817–1843.

Easley, D., and M. O'Hara. 2010. "Liquidity and Valuation in an Uncertain World." *Journal of Financial Economics* 97, no. 1: 1–11.

Edmans, A. 2023. "The End of ESG." *Financial Management* 52, no. 1: 3–17.

Ter Ellen, S., W. F. C. Verschoor, and R. C. J. Zwinkels. 2019. "Agreeing on Disagreement: Heterogeneity or Uncertainty?" *Journal of Financial Markets* 44: 17–30.

Fidelity. (2024). *Sustainability Update: Sustainability Remains Fundamental*. https://www.fidelity.com.cn/media/PDF/esg/Fidelity_SI_report_2024_HK.pdf.

Flood, C. (2020). SEC Chair Warns of Risks Tied to ESG Ratings. *Financial Times*. https://www.ft.com/content/2c662135-4fd3-4c1b-9597-2c6f8f17faed.

Frankel, R., and X. Li. 2004. "Characteristics of a Firm's Information Environment and the Information Asymmetry Between Insiders and Outsiders." *Journal of Accounting and Economics* 37, no. 2: 229–259.

Garfinkel, J. A. 2009. "Measuring Investors' Opinion Divergence." *Journal of Accounting Research* 47, no. 5: 1317–1348.

Gibson Brandon, R., P. Krueger, and P. S. Schmidt. 2021. "ESG Rating Disagreement and Stock Returns." *Financial Analysts Journal* 77, no. 4: 104–127.

Gilboa, I., and D. Schmeidler. 1989. "Maxmin Expected Utility With Non-Unique Prior." *Journal of Mathematical Economics* 18, no. 2: 141–153.

Global Sustainable Investment Alliance. (2022). *Global Sustainable Investment Review*. https://www.gsi-alliance.org/wp-content/uploads/2023/12/GSIA-Report-2022.pdf.

Global Sustainable Investment Alliance, Principles for Responsible Investing, and CFA Institute. (2024). *Definitions for Responsible Investment Approaches*. https://rpc.cfainstitute.org/-/media/documents/article/industry-research/definitions-for-responsible-investment-approaches.pdf.

GRI. (2022). *Our Mission and History*. https://www.globalreporting.org/about-gri/mission-history/.

Halper, J., D. Grieve, S. Bussiere, T. Shriver, and J. Balakrishnan. 2023. "ESG Ratings: A Call for Greater Transparency and Precision." *Corporate Governance Advisor* 31, no. 1: 1–19.

Harris, M., and A. Raviv. 1993. "Differences of Opinion Make a Horse Race." *Review of Financial Studies* 6, no. 3: 473–506.

Heinkel, R., A. Kraus, and J. Zechner. 2001. "The Effect of Green Investment on Corporate Behavior." *Journal of Financial and Quantitative Analysis* 36, no. 4: 431–449.

Holod, D., and J. Peek. 2007. "Asymmetric Information and Liquidity Constraints: A New Test." *Journal of Banking & Finance* 31, no. 8: 2425–2451.

Hong, H., and M. Kacperczyk. 2009. "The Price of Sin: The Effects of Social Norms on Markets." *Journal of Financial Economics* 93, no. 1: 15–36.

Hong, H., and J. C. Stein. 2007. "Disagreement and the Stock Market." *Journal of Economic Perspectives* 21, no. 2: 109–128.

Huang, D., J. Li, and L. Wang. 2021. "Are Disagreements Agreeable? Evidence From Information Aggregation." *Journal of Financial Economics* 141, no. 1: 83–101.

Kandel, E., and N. D. Pearson. 1995. "Differential Interpretation of Public Signals and Trade in Speculative Markets." *Journal of Political Economy* 103, no. 4: 831–872.

Karpoff, J. M. 1986. "A Theory of Trading Volume." *Journal of Finance* 41, no. 5: 1069–1087.

Kim, O., and R. E. Verrecchia. 1991. "Trading Volume and Price Reactions to Public Announcements." *Journal of Accounting Research* 29, no. 2: 302–321.

Kim, O., and R. E. Verrecchia. 1997. "Pre-Announcement and Event-Period Private Information." *Journal of Accounting and Economics* 24, no. 3: 395–419.

Kimbrough, M. D., X. Wang, S. Wei, and J. Zhang. 2024. "Does Voluntary ESG Reporting Resolve Disagreement Among ESG Rating Agencies?" *European Accounting Review* 33, no. 1: 15–47.

Knight, F. 1921. Risk, Uncertainty and Profit *(Vol. Chapter VII)*. Houghton Mifflin.

Larcker, D. F., L. Pomorski, B. Tayan, and E. M. Watts (2022a). ESG Ratings: A Compass without Direction. https://ssrn.com/abstract=4179647.

Larcker, D. F., B. Tayan, and E. M. Watts. 2022b. "Seven Myths of ESG." *European Financial Management* 28, no. 4: 869–882.

Li, D., and G. Li. 2021. "Whose Disagreement Matters? Household Belief Dispersion and Stock Trading Volume." *Review of Finance* 25, no. 6: 1859–1900.

Lizárraga, J. (2022). *Meeting Investor Demand for High Quality ESG Data*. U.S. Securities and Exchange Commision. https://www.sec.gov/newsroom/speeches-statements/lizarraga-speech-meeting-investor-demand-high-quality-esg-data.

LSEG. (2024). *LSEG ESG Scores*. London Stock Exchange Group. https://www.lseg.com/en/data-analytics/sustainable-finance/esg-scores.

Miller, E. M. 1977. "Risk, Uncertainty, and Divergence of Opinion." *Journal of Finance* 32, no. 4: 1151–1168.

Moss, A., J. P. Naughton, C. Wang, and I. Yeung (2022). Investor Integration of Earnings and ESG News. https://doi.org/10.2139/ssrn.4266302.

MSCI. (2024a). *Optimizing ESG Factors in Portfolio Construction*. https://www.msci.com/www/webcast/optimizing-esg-factors-in/013734495.

MSCI. (2024b). *What MSCI's ESG Ratings Are and Are Not*. Morgan Stanley Capital International. https://www.msci.com/our-solutions/esg-investing/esg-ratings/what-esg-ratings-are-and-are-not.

O'Hara, M. 2003. "Presidential Address: Liquidity and Price Discovery." *Journal of Finance* 58, no. 4: 1335–1354.

Palley, A. B., T. D. Steffen, and X. F. Zhang. 2024. "The Effect of Dispersion on the Informativeness of Consensus Analyst Target Prices." *Management Science* 71, no. 3: 1865–1888.

Pástor, Ľ., R. F. Stambaugh, and L. A. Taylor. 2021. "Sustainable Investing in Equilibrium." *Journal of Financial Economics* 142, no. 2: 550–571.

Pedersen, L. H., S. Fitzgibbons, and L. Pomorski. 2021. "Responsible Investing: The ESG-Efficient Frontier." *Journal of Financial Economics* 142, no. 2: 572–597.

Rzeźnik, A., K. W. Hanley, and L. Pelizzon (2022). Investor Reliance on ESG Ratings and Stock Price Performance. https://doi.org/10.2139/ssrn.3801703.

SASB. (2016). *SASB Completes Provisional Standards for All Industries of the Economy; Launches Next Phase of Standards Development*. https://www.prnewswire.com/news-releases/sasb-completes-provisional-standards-for-all-industries-of-the-economy-launches-next-phase-of-standards-development-300247229.html?tc=eml_cleartime.

SASB. (2024). *SASB Standards Overview*. Sustainability Accounting Standards Board (IFRS Foundation). https://sasb.ifrs.org/standards/.

Schneemeier, J. 2023. "Voluntary Precision Disclosure and Endogenous Market Feedback." *Management Science* 69, no. 9: 5618–5637.

Serafeim, G., and A. Yoon. 2023. "Stock Price Reactions to ESG News: The Role of ESG Ratings and Disagreement." *Review of Accounting Studies* 28, no. 3: 1500–1530.

Shanaev, S., and B. Ghimire. 2022. "When ESG Meets AAA: The Effect of ESG Rating Changes on Stock Returns." *Finance Research Letters* 46: 102302.

Sprenger, T. O., A. Tumasjan, P. G. Sandner, and I. M. Welpe. 2014. "Tweets and Trades: The Information Content of Stock Microblogs." *European Financial Management* 20, no. 5: 926–957.

Starks, L. T. 2023. "Presidential Address: Sustainable Finance and ESG Issues—Value Versus Values." *Journal of Finance* 78, no. 4: 1837–1872.

Sustainalytics. (2024). *About Sustainalytics ESG Risk Ratings*. Sustainalytics. https://www.sustainalytics.com/esg-data.

TCFD. (2017). *Recommendations of the Task Force on Climate-Related Financial Disclosure*. https://assets.bbhub.io/company/sites/60/2021/10/FINAL-2017-TCFD-Report.pdf.

Tkac, P. A. 1999. "A Trading Volume Benchmark: Theory and Evidence." *Journal of Financial and Quantitative Analysis* 34, no. 1: 89–114.

Vanguard. (2023). *Vanguard's Approach to ESG*. https://www.vanguard.co.uk/content/dam/intl/europe/documents/en/vanguards-approach-to-esg-uk-en-pro.pdf.

Varian, H. R. 1985. "Divergence of Opinion in Complete Markets: A Note." *Journal of Finance* 40, no. 1: 309–317.

Xiong, W. (2013). Bubbles, Crises, and Heterogeneous Beliefs. https://ssrn.com/abstract=2237818.

Zhang, X. F. 2006a. "Information Uncertainty and Analyst Forecast Behavior." *Contemporary Accounting Research* 23, no. 2: 565–590.

Zhang, X. F. 2006b. "Information Uncertainty and Stock Returns." *Journal of Finance* 61, no. 1: 105–137.

Supporting Information

Additional supporting information can be found online in the Supporting Information section.
supmat.

Appendix A

Disagreement models emerged to account for differences in how investors form their beliefs. Kim and Verrecchia (1991) introduced a model where investors share common starting beliefs but have varying levels of confidence in those beliefs due to private information. In this model, trading occurs as investors adjust their views when new public information becomes available. Although rationality assumes common initial beliefs, Acemoglu et al. (2016) showed that uncertainty about how public signals is distributed can lead to differing beliefs. Overconfidence is another source of disagreement, as investors may overly trust their own judgement, sometimes overreacting to unreliable public signals (Xiong 2013).

Other models explore how investors interpret the same public information in different ways. Kim and Verrecchia (1997) found that belief changes drive trading volume, which is further influenced by differing interpretations of information. Harris and Raviv (1993) suggested that investors update their beliefs differently based on their own frameworks, while Kandel and Pearson (1995) showed that trading can result purely from varying interpretations of the same data, such as during earnings announcements. Empirical evidence from Cookson and Niessner (2020) confirms this, showing that different investment models can produce diverse viewpoints.

Banerjee and Kremer (2010) developed a dynamic disagreement model where trading behaviour shifts as disagreement evolves. In their model, greater disagreement leads to individualistic trading based on diverse interpretations, while reduced disagreement causes convergence trading as investors align their beliefs with new information. Over time, individualistic trading diminishes due to rising uncertainty, while convergence trading becomes more prominent as disagreements narrow.

In addition to differing beliefs and interpretations, another direct source of disagreement is information asymmetry, where different investors have access to different information (Cookson and Niessner 2020). Two main factors are gradual information flow and limited attention. Information flow causes some investors to receive updates sooner than others, leading to differences in beliefs and trading opportunities. Limited attention, due to distractions or overload, makes investors focus only on parts of public information, further increasing information asymmetry and disagreement (Hong and Stein 2007).

Beyond examining the sources of disagreement and their impact on trading, research also explores how disagreement influences returns. Two main theories address this. Miller (1977) argued that disagreement leads to optimistic valuations dominating the market, especially under short-selling constraints, which prevent pessimistic views from affecting prices. This results in inflated prices and lower returns. Conversely, Varian (1985) and Barron and Stuerke (1998) proposed that disagreement increases uncertainty, causing investors to demand higher returns. Atmaz and Basak (2018) reconciled these perspectives, suggesting that in highly optimistic markets, disagreement amplifies optimism, consistent with Xiong (2013) "resale option" theory. This theory suggests that investors overvalue assets in anticipation of selling them to even more optimistic buyers, contributing to asset bubbles. Huang et al. (2021) found that during periods of high optimism (indicated by high sentiment and strong growth forecasts), the relationship between disagreement and returns becomes negative. This is relevant to our study, as it demonstrates that the impact of disagreement on asset pricing depends on whether it stems from uncertainty or belief heterogeneity.

Similarly, disagreement's effect on trading depends on its cause; uncertainty or belief heterogeneity (Ter Ellen et al. 2019). Belief heterogeneity generally increases trading (e.g. Banerjee and Kremer 2010; Booker et al. 2023; Cookson and Niessner 2020; Karpoff 1986; Li and Li 2021; Varian 1985). However, if disagreement arises from information uncertainty, it decreases trading (De Castro and Chateauneuf 2011; Easley and O'Hara 2009; Easley and O'Hara 2010).

Knight (1921) distinguishes the concept of uncertainty where individuals have unknown odds about future states from the concept of risk where the odds are known. Investors behave differently when faced with risk versus Knightian uncertainty. Increase in risk, despite raising the cost of capital, does not discourage investors from trading. However, in the case of uncertainty, investors do not have knowledge about the distribution of expected returns and, thus, have no prior belief about different future occurrences.

To explain investors' behaviour under this uncertainty, Gilboa and Schmeidler (1989) introduced a model where individuals try to maximise their expected utility. This utility maximisation assumption leads them to start disposing off ambiguous assets. However, such action triggers more trading and does not explain the decline in trading or complete non-participation during periods of high uncertainty (Easley and O'Hara 2010). Bewley (2002) drops the complete preference assumption and introduces an "inertia" assumption where investors trade only if there is a change in their status quo from trading. According to the model, an investor will invest in an asset only if it has a higher expected value across many probability distributions. This incomplete preference over portfolio selection, in turn, results in ambiguity averse investors to remain on the status quo; that is, trading less or even not participating in periods of extreme uncertainty such as the 2007–2008 financial crisis (Easley and O'Hara 2010).

TABLE A1 | Variables' definitions and data sources.

Variable	Definition	Source
AbLogTurnover	Abnormal log turnover: calculated as the natural logarithm of trading volume divided by the number of shares outstanding for firm i in month t (gross turnover), minus its median over the period t–7 and t–2.	CRSP
AbMaLogTurnover	Abnormal market-adjusted log turnover: calculated as the difference between market-adjusted log turnover for firm i in month t and its median over the period t–7 and t–2. Market-adjusted log turnover is the difference between the natural logarithms of a firm's turnover and market turnover (calculated as total shares traded in the market divided by total shares outstanding during month t).	CRSP
LogTurnover	Gross Trading Volume: calculated as the natural logarithm of trading volume divided by the number of shares outstanding for firm i in month t.	CRSP
Log(DISP)	Analysts Forecasts Dispersion: calculated as the natural logarithm of standard deviation of 1-year EPS forecasts scaled by the absolute value of mean forecast for firm i in month t–1.	IBES
ESG_DISG	ESG ratings' disagreement: calculated as the average of the pairwise standard deviations between the percentile ranks of monthly ESG scores (pertaining to ESG performance of month t–1) for firm i during month t provided by the three ESG rating providers: MSCI-IVA, LSEG-ESG, and Sustainalytics.	MSCI-IVA, LSEG-ESG, and Sustainalytics
STD_ESG_DISG	*ESG_DISG* standardised to have 0 mean and 1 standard deviation.	MSCI-IVA, LSEG-ESG, and Sustainalytics
SIZE	Firm size: calculated as the natural logarithm of total assets as of the end of quarter t–1.	Compustat
ROA	Return on assets: calculated as the quarterly operating income after depreciation divided by total assets as of the end of quarter t–1.	Compustat
MTB	Market-to-book ratio: calculated as the product of quarterly close price and the number of common shares outstanding divided by the book value of total common equity as of the end of quarter t–1.	Compustat
LEV	Leverage: calculated as the total of quarterly debt in current liabilities and long-term debt divided by total assets as of the end of quarter t–1.	Compustat
ANALYSTS	Number of EPS 1-year forecast estimates for firm i in month t.	IBES
INST_OWNERSHIP	Institutional ownership percentage: calculated as the number of shares owned by institutional investors divided by total shares outstanding for firm i in quarter t multiplied by 100.	Thomson Reuters 13F
VOLATILITY	Volatility: calculated as the standard deviation of daily returns for firm i during month t.	CRSP
SPREAD	Bid-Ask Spread: the relative bid-ask spread for firm i in month t measured as (ask-bid)/((ask+bid)/2).	CRSP