The Demand, Supply, and Market Responses of Corporate ESG Actions: Evidence from a Nationwide Experiment in China*

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We conducted a nationwide field experiment with 4,800+ Chinese-listed companies, randomly raising ESG concerns to their management teams via high-visibility and high-stakes online platforms. Tracking the full impact-generating process, we find that companies respond to our concerns by providing high-quality answers, publishing ESG reports, and making commitments to investors. Over time, Environmental (E) inquiries boost stock valuations, while Governance (G) concerns prompt skepticism. Productive and opaque firms are more likely to respond, consistent with a signaling model where costly ESG actions signal firm quality under information asymmetry. Overall, ESG actions are likely driven by profit-oriented signaling rather than values-based motives.

Keywords: Information Asymmetry, Environmental, Social, and Governance (ESG), Corporate Social Responsibility (CSR), Shareholder Engagement

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I. Introduction

Public pressure has long been a powerful force in shaping corporate pro-social behavior (Buntaine et al., 2024; Egorov & Harstad, 2017; Harrison & Scorse, 2010). From the consumer rights movements of the 1960s to the shareholder activism of the 1980s, shifts in public sentiment have repeatedly pressured firms to adopt higher standards of social responsibility and accountability. In recent decades, this dynamic has intensified with the rise of corporate social responsibility (CSR) and environmental, social, and governance (ESG) practices, which increasingly enter core decision margins in boardrooms and capital markets (Allcott et al., 2023; Bénabou & Tirole, 2010; Flammer et al., 2021; Kitzmueller & Shimshack, 2012). Yet, despite this surge in attention, firms face a fundamental dilemma: how to reconcile mounting public and investor demands for social responsibility with the imperative to maintain profitability and shareholder value. This challenge is further complicated by striking heterogeneity in CSR/ESG expectations across countries, industries, and even among stakeholder groups within firms (Dyck et al., 2019; Jensen, 2002).

In this context, this paper examines three central questions in the economics of corporate behavior: How do firms respond to divergent public demand for ESG improvements? Why do some firms pursue ambitious pro-social initiatives while others exert only minimal effort or resist altogether? What are the market implications for firms pursuing aggressive ESG performance? Traditional economic theory, epitomized by Milton Friedman (1970), posits that a firm's sole responsibility is to maximize shareholder value. However, the rise of stakeholder theory (Freeman, 1984) and the proliferation of ESG metrics have challenged this paradigm, arguing that firms should also account for the interests of employees, customers, and society at large. Empirically, the effects of those pro-social initiatives remain contested: while some firms reap reputational and financial rewards from ESG efforts (Dhaliwal et al., 2011; Elfenbein & McManus, 2010), others face backlash or negligible effects, raising critical questions about the drivers and consequences of ESG adoption (Cassar & Meier, 2021; Colonnelli et al., 2024).

To credibly answer these questions, we conduct a nationwide field experiment involving all non-financial listed firms (>4,800) in China. We raise ESG-related concerns to randomly selected firms through two online platforms operated by the Shenzhen and Shanghai Stock Exchanges, which host over 88,000 active accounts and allow retail investors to communicate directly with corporate management. These platforms ensure high visibility, as questions and responses are publicly archived and scrutinized by a broad audience of retail investors, institutional asset managers, and analysts. Furthermore, securities regulations mandate that listed firms provide a timely response, making our intervention a salient and material event for the management team. By randomly assigning firms to receive inquiries about specific Environmental (E), Social (S), or Governance (G) issues, we mimic real-world heterogeneity in ESG expectations and introduce an exogenous demand shock to causally identify its impacts on various market participants.

We then follow the entire impact-generating process—from online to offline—and assess whether and how demand translates into supply and equilibrium effects. This includes firms' direct responses to our inquiries, their subsequent actions, spillovers to other stakeholders, and ultimately stock market reactions. We observe that many firms actively address our concerns by disclosing detailed ESG information and outlining future strategies. These firms are more likely to reference ESG under other topics, release ESG reports, and highlight ESG in communications with institutional investors after our experiment. However, not all ESG efforts translate into market value: while environmental and social initiatives elicit positive investor reactions, governance information is often treated as a warning sign, resulting in divergent price trajectories. While our initial intervention represents a relatively small demand shock compared to major reputation events (Akey et al., 2023), the subsequent corporate actions, changes in ESG ratings, and capital flows collectively generate the gradual but persistent stock price movements over time.

To further understand the underlying motives for ESG actions, we develop a simple conceptual model based on the classical Spence (1973) signaling framework. We incorporate ESG as an image-enhancing signal that aligns with profit-maximization goals and empirically test the model predictions using the experimental data. Intuitively, productive firms adopt costly ESG actions as a strategy to reveal their quality under information asymmetry. Consistent with the theory predictions, we find that firms with higher productivity, greater information barriers, and more ESG-conscious investors are more likely to rely on ESG signals. These firms also reap the largest market benefits from their signaling behaviors in equilibrium. In contrast, values-driven motivations, such as leader characteristics and cultural factors, appear to play a relatively minor role in explaining the heterogeneity of ESG behaviors among Chinese firms.

This paper makes four key contributions to the literature. First, we provide the first nation-scale field experimental evidence on how exogenous ESG demand shocks propagate through corporate decisions to market equilibria. While prior work has extensively studied CSR/ESG through observational lenses—exploiting regulatory changes, reputation shocks, or regression discontinuities—they may face challenges in disentangling endogenous demand shifts from firms' strategic responses (see Gillan et al. (2021) and Kitzmueller and Shimshack (2012) for recent reviews). Among the few experimental designs, Bartling et al. (2024) explore the role of public discourse in pro-social market behaviors in a lab setting. Burbano (2016), List and Momeni (2021), and Colonnelli et al. (2023) analyze ESG decisions within individual firms. Boudreau (2024) studies multi-firm ESG behavior but only focuses on compliance with safety standard mandates. In contrast, our nationwide field experiment, encompassing over 4,800 Chinese listed firms, enables causal identification of how heterogeneous ESG preferences shape strategic interactions among various market participants. We directly address the "black box" critique of ESG studies (Pollman, 2024), revealing general equilibrium effects across industrial and administrative boundaries. Moreover, we unpack the information diffusion process and establish clear causal links in the dynamic interplay between corporate disclosures and stakeholder reactions (Alatas et al., 2016).

Second, we extend traditional corporate valuation frameworks by demonstrating how investors' non-pecuniary preferences reshape equilibrium outcomes (Barber et al., 2021; Green & Roth, 2025). While standard models assume prices reflect only cash-flow fundamentals (Fama, 1970), growing evidence suggests ESG attributes systematically affect asset pricing (Pástor et al., 2021; Pedersen et al., 2021). We contribute to this discussion by uncovering significant variations in market responses across ESG dimensions. Our positive market reactions to E/S concerns align with models of individual altruism (Bénabou & Tirole, 2006, 2010) and social norms (Hong & Kacperczyk, 2009). In contrast, negative responses to G concerns reflect agency costs (Gompers et al., 2003; Jensen & Meckling, 1976) or managerial myopia (Stein, 1989). Taken together, these findings provide micro-foundations for dimension-specific ESG regulations (Pollman, 2024).

Third, we advance organizational economics and corporate strategy by formalizing ESG adoption as a profit-maximizing response to information frictions. Classic signaling models (Spence, 1973) posit that firms use observable but costly actions—such as debt (Ross, 1977), dividends (Bhattacharya, 1979), advertising (Milgrom & Roberts, 1986), or charity (Elfenbein et al., 2012)—to credibly disclose private information. We extend this framework by showing that ESG actions serve a similar role (Lys et al., 2015), particularly for high-productivity firms facing high information asymmetry. This framework reconciles the competing goals of profit maximization and social responsibility, suggesting that firms can "do well by doing good" under market frictions (Eichholtz et al., 2010; Waddock & Smith, 2000). Furthermore, our analysis addresses Starks' (2023) call to distinguish value-driven motives from values-driven explanations of ESG decision-making. The findings underscore the importance of financial incentives in corporate sustainability practices.

Lastly, we create a persuasive example of how individuals can be empowered to promote pro-social corporate actions. While institutional investors are widely recognized for their significant influence on corporate decisions (Appel et al., 2016; Dyck et al., 2019), retail investors—often referred to as "diffused shareholders"—have traditionally been viewed as having limited control or impact (Shleifer & Vishny, 1997). Recent research, however, highlights the potential of public citizen appeals to drive meaningful corporate change, especially in information disclosure (Wong et al., 2023) and pollution reduction (Buntaine et al., 2024; Wong et al., 2024). Building on these insights, our field experiment expands the scope of inquiry to broader corporate governance, demonstrating that strategic use of public communication channels can exert significant enforcement pressures on firms (Broccardo et al., 2022). These pressures not only yield measurable outcomes but also represent a scalable, low-cost complement to regulatory interventions. Importantly, the voices of retail investors serve dual roles: they act as demand signals for corporate accountability and provide valuable information for firms to reassess their market payoffs.

The rest of this paper is structured as follows. Section II describes our research settings. Section III provides an overview of the experimental design. Section IV introduces the data, presents balance tests, and outlines our empirical strategy. Section V and Section VI report the experimental results. Section VII examines the underlying motives behind firms' ESG actions by developing a signaling framework and testing its predictions. Finally, Section VIII concludes.

II. Research Settings

II.1 Online Q&A Platforms

In this study, we make use of two unique online Q&A platforms in China. Unlike developed economies, China has over two hundred million retail investors in its stock market. Retail investors hold 30% of the free-float market value of the A-share companies and account for over 60% of the trading volume (Li, 2024; Quan, 2022). To facilitate communication between retail investors and listed firms, the Shenzhen and Shanghai Stock Exchanges established official Q&A platforms in 2010 and 2013 (see Figure A1). Each A-share firm has its own community page and is required to appoint a senior employee (typically the board secretary) to ensure response accuracy. When a question is posted, both management and the firm's followers receive alerts, with followers notified again once the firm replies. The platforms prohibit disclosure of material new information but are dedicated to explaining existing disclosures in a publicly accessible manner.

As an indispensable channel of first-hand information, the two platforms have attracted significant interest from retail investors. As of 2023, over 450,000 questions are posted on these two platforms annually, equivalent to more than 9,000 questions per week. Almost all (>98%) A-share firms have joined the platforms, and the overall reply rate exceeds 85%. Response time varies significantly by firm efficiency, ranging from a few hours to over a month, with a mean of 10 days and a median of just 3 days. Overall, the two platforms play an important role in bridging businesses and people. Executives now have direct access to public opinion and can swiftly respond to individual concerns as a result of this new information channel.

Several studies have examined the effectiveness of these online platforms. Evidence suggests that such platforms can enhance market informativeness (Lee & Zhong, 2022), discourage opportunistic reporting (Li et al., 2023), and improve corporate investment efficiency (Xu et al., 2024). They may also strengthen shareholder influence, as dividend-related questions is positively associated with future dividend payouts (Lin et al., 2023). Although these studies offer valuable preliminary insights into the influence of retail investor communication, their non-experimental designs render the findings susceptible to self-selection bias.

To address this concern, a small set of experimental studies—Wang et al. (2022), Wong et al. (2023), and Wong et al. (2024)—apply randomized interventions on the same platforms, finding that retail investor demands can increase dividends, improve transparency, and reduce emissions. Our study extends this literature along four dimensions. First, our experiment covers the entire universe of non-financial listed firms in China, providing unmatched scale, generalizability, and statistical power. Second, we tailor inputs with firm-specific information to mimic real investor concerns and enable granular heterogeneity analysis, showing how productivity, information opacity, and investor clientele shape ESG responses. Third, by randomizing emphasis across E, S, and G dimensions, we identify how and why market reactions diverge across ESG facets. Finally, we move beyond single outcomes to trace the full impact-generating process from online engagement to corporate action and market valuation. As the first large-scale ESG social experiment in China, we systematically document the demand-supply dynamics of this ever-growing issue and generate social influence far beyond the scope of these platforms.

II.2 Stock Forums and Social Media

A complementary design to raising questions on Q&A platforms is forwarding the interactions to stock forums and social media. While Q&A platforms primarily engage management teams, stock forums and social media amplify discussions among retail investors and the general public. This interplay allows us to assess the role of public sentiment in shaping corporate decisions. We consider three platforms when forwarding the messages: Guba, Xueqiu, and Weibo.

The first two are prominent stock forums where retail investors exchange ideas and investment strategies. Guba (Guba.EastMoney.com, shown in Panel A of Figure A2) is one of the most active stock message boards globally and the most influential in China (Li & Zhang, 2023). It has been widely used in academic studies as a proxy for public attention (Jiang et al., 2022), investor communications (Jiang et al., 2019), and crowd criticisms (Ang et al., 2021). Xueqiu (xueqiu.com, shown in Panel B of Figure A2) is another popular and representative financial community in China. It houses professional knowledge exchanges and stock advice that are welcomed by relatively inexperienced investors. Several studies have used sentiment analyses of Xueqiu posts to explore their impacts on stock market returns and volatility (Tham, 2015).

The last platform, Weibo, is China's equivalent of X (formerly Twitter) (see Figure A3). With 500–600 million active users and over 38,000 verified media accounts (Weibo, 2020), it plays a vital role in shaping public opinions (Zheng et al., 2019) and coordinating collective actions (Qin et al., 2024). Although ESG-related posts are relatively rare, Weibo's interactive features, such as mentioning (@) and tagging (#), enable engagement with a broad audience, including consumers, suppliers, activists, and community members. By forwarding messages to these platforms, we aim to increase public awareness and spark broader discussions beyond firm–investor interactions.

III. Experimental Design

We conducted a nationwide randomized controlled trial (RCT) on listed companies in China to examine how firms respond to ESG-related public concerns. Our sample focuses on non-financial A-share firm that received at least one question on either of the two Q&A platforms in 2023. To avoid unwarranted criticism of their ESG commitments, we exclude industry leaders that rank first in ESG ratings across rating agencies. The final sample comprises 4,852 firms from 29 industries.

Figure 1 summarizes the experimental design. Using stratified randomization by market value, we assign firms to a control group (40% of the sample) or one of four treatment groups (15% each). Control firms receive no intervention. Treatment 1 (T1) provides only aggregate ESG ratings from leading agencies (see Data section for details). Treatments 2–4 (T2–T4) combine these ratings with targeted critiques of their environmental (T2), social (T3), or governance (T4) performance, respectively. All messages are intentionally crafted with a negative tone to motivate further efforts.[1] To enhance credibility and relevance, we include comparative advantages within the industry and recent ESG-related news in all messages. Sample questions can be found in

[1] It is important to note that our treatment arms are not conditioned on ESG ratings or E/S/G sub-ratings. In other words, firms across different treatment arms are *ex-ante* balanced, with no statistically significant differences in their ESG performance. To ensure the negative tone of our experimental messages, we selectively reference ratings from agencies that assign low scores to the treated firms. This approach is feasible due to the relatively low correlation in ESG ratings across different agencies, a phenomenon well documented by Berg et al. (2022).

Appendix A. The experiment ran from December 4, 2023, to April 1, 2024, during which a team of 20 research assistants posted 5,908 questions to 2,945 treated firms (see Appendix B for implementation details).

In addition to the main treatment arms, we establish two crosscut arms to examine the role of investors' ESG preferences in shaping firm behavior. In C1A, interactions occur exclusively with firm management teams via the Q&A platforms (60% of treated firms). In C1B, we amplify exposure by forwarding our interactions with firms to two investor forums (Guba and Xueqiu) and social media (Weibo) (40% of treated firms). These forwarded messages use a neutral tone to elicit authentic investor reactions. We then apply natural language processing to quantify the sentiment of investors' comments on our posts and examine whether these sentiments predict firms' platform responsiveness or market valuations.

We track the full impact-generating process of our experiment, as illustrated in Figure 2. We begin by establishing a comprehensive baseline of firms' ESG performance, including aggregate ESG ratings, E/S/G subcomponent scores, historical ESG disclosures, and ESG-related media coverage. These baseline metrics inform the evidence-based ESG critiques we post on the platforms. Throughout the experiment, we monitor several dimensions of platform activity, including firms' direct responses to our questions, follow-up ESG inquiries from other users, and spillover effects into non-ESG discussions. We complement these online measures with sentiment analysis of forum and social media discussions under our forwarded messages. Beyond online behavior, we track offline responses such as ESG reports, communications with institutional investors, and subsequent third-party evaluations. Finally, we measure market impacts through daily stock indicators. This multi-tiered measurement framework allows us to identify: (1) direct treatment effects on firm behavior, (2) secondary reactions from market participants, (3) broader market adjustments, and (4) ultimate equilibrium effects on stock valuations. Together, they provide a complete picture of the demand-supply dynamics in the ESG market.

Prior to designing this experiment, we have carefully considered its ethical implications. First, both the Shenzhen and Shanghai Stock Exchange explicitly encourage investors to post questions on their online Q&A platforms. There are, on average, over 9,000 questions per week, and our experiment adds <5% of questions to the ongoing discussions. Second, the Chinese government has been advocating for full coverage of ESG disclosure for central enterprises (SASAC, 2024). Our efforts to motivate firms to disclose more ESG information are consistent with the Chinese government's policy direction. Third, we consulted with several institutional investors and active users of online platforms and were not advised of any repercussions of ESG-related posts. Finally, although we collected no individual-level data, we obtained ethics approval from the Human Research Ethics Committee at the University of Hong Kong (Project ID: EA240235).

IV. Data and Empirical Specifications

IV.1 Data

Data in this study comes from four main sources: financial terminals, company websites, data vendors, and web scraping. This section briefly discusses the variables derived from each source.

Firm characteristics: We collect a comprehensive set of characteristics for China's A-share firms using the CSMAR Database and Wind Financial Terminal. Basic information includes firms' location, industry, age, employees, and market value. To measure productivity, we use return on assets (ROA) and return on equity (ROE) and calculate value-added-based and revenue-based total factor productivity (TFP) using data on depreciation, labor compensation, revenue, and operating costs (see Appendix H for methodological details). For transparency, we draw on 16 established measures such as equity structure, supply chain concentration, and board independence (see Appendix I). For leader traits, we use the CSMAR director database to obtain information on chairpersons, vice-chairpersons, CEOs, and vice-CEOs, who are equivalent to U.S. "C-Suite" executives (Fisman & Wang, 2015). For cultural factors, we link headquarter locations and leaders' hometowns to city-level historical data from Chen et al. (2020) and Chen et al. (2022).

Online interactions: We regularly monitor and scrape data from the Q&A platforms, stock forums, and social media (Weibo). From Q&A platforms, we collect firms' response rate, time, length, and content, including replies to both our and other users' questions. We also capture spillovers by tracking ESG keywords in unrelated discussions (see Appendix D for a complete ESG dictionary). From forums and social media, we gather all comments and follow-up discussions on our forwarded posts and conduct sentiment analysis to gauge public opinion.[2]

Quarterly ESG ratings: ESG ratings serve as a key outcome, reflecting firm performance across various dimensions. We collect quarterly ratings from both domestic (Syntao, Wind, CSIndex, Sino-Securities Index, RKS) and foreign (MSCI, Refinitiv, FTSE, Bloomberg, S&P Global) agencies, including sub-ratings and indicator values when available. These ratings informed the ESG critiques in our experiment. After the RCT, we obtained access to the iFind Terminal

[2] We note that a subset of forwarded posts became subject to community reporting and subsequent removal by platform moderators, resulting in incomplete web-scraped results for platform interactions. This affects only 16 firms (1.36% of the C1B sample) and does not meaningfully affect our core estimates. To the extent this occurs, any bias would attenuate treatment effects toward zero, implying our reported estimates likely represent conservative bounds for the true effects of investor feedback.

and collected historical ESG data from additional agencies such as QuantData and Hithink RoyalFlush. These new sources allow us to test whether firms enhance their ESG performance in a neutral manner, as observed by agencies not referenced in our interventions.

ESG-related offline actions: In addition to ESG ratings, we examine three dimensions of firms' ESG offline actions: release and quality of ESG reports, ESG-related news coverage, and ESG discussions with institutional investors (such as during site visits and interviews). For the first two dimensions, we collaborate with a data vendor called YoujiVest to scrape firm websites and mainstream media regularly. This allows us to obtain all historical ESG reports in PDF format and use OCR techniques to access their contents and construct quality measures. We also create a daily measure of negative media coverage related to regulation violations and supply chain issues for each listed firm. For institutional investor communications, we use the CSMAR database, which records the date, target firm, institution name, participants, and transcript of each interaction. We separate firm responses from investor questions using GPT and identify ESG mentions via a keyword search (see Appendix E for details).

IV.2 Balance Tests

We conducted a series of balance tests prior to the experiment, as presented in Table 2. We examine firm-level characteristics spanning (1) basic attributes (firm age, employees, market value, and ROA), (2) prior platform engagement (investor inquiries and follower counts), and (3) pre-existing ESG performance (historical ESG reports, ESG discussions with institutional investors, third-party ratings, and media coverage). For each variable, we report treatment and crosscut group means alongside t-statistics and p-values for differences against the control. All comparisons yield statistically insignificant differences ($p > 0.05$), indicating that we cannot reject the null hypothesis that the treated and control firms are statistically identical. Therefore, firm-level characteristics are balanced across experimental arms, confirming that the randomization was well executed.

IV.3 Descriptive Patterns

Table 1 provides an overview of the characteristics of the Shenzhen and Shanghai Q&A platforms over the 11 months leading up to our experiment. Each platform contributes approximately 50% of the firms in our study, totaling 4,852 firms that received at least one question. On average, firms on the Shenzhen platform received 105 questions during this period, with the number of questions ranging from one to 1,270. While firms on the Shanghai platform received fewer questions on average, the maximum number of questions per firm reached 3,587. Both platforms saw high engagement: firms responded to over 80% of questions within one to two weeks, with average reply lengths of around 100 Chinese characters (equivalent to a short paragraph).

Among the 393,676 questions in 2023, the majority focused on operational topics (production, technology, business development), representing 58.61% in Shenzhen and 51.14% in Shanghai. Financial management (earnings, dividends, asset restructuring) and stock trading comprised the next largest categories, collectively accounting for 30-40% of questions on both platforms. ESG-related questions (broadly defined as those containing ESG/CSR keywords or addressing specific ESG dimensions) constituted 5-7% of inquiries and were predominantly around governance issues such as board structure and executive compensation. Among them, fewer than 0.1% of questions explicitly mentioned ESG or CSR, and only seven (<0.01%) referenced ESG ratings.

Overall, the summary statistics confirm the characteristics of the platforms highlighted in previous sections. First, firms place great importance on these platforms, providing high-quality responses within a relatively short time frame. Second, investors are highly active, with approximately 9,000 questions posted weekly, indicating a substantial and non-negligible potential audience for our messages. Third, there was limited public interest in ESG topics prior to our experiment, as evidenced by the minimal number of investor queries on ESG. Therefore, these platforms offer an excellent setting to examine firms' supply-side responses to new public demand.

Our experiment has led to non-negligible attention and interaction across platforms. By the end of our data collection period (June 30, 2024), we had received 4,992 responses from listed firms, resulting in a response rate of 84.5%. The median reply time was four days, and 24.88% of the questions were answered within a day. Response length exhibited significant heterogeneity, ranging from 5 to 1,086 Chinese characters, with a median of 123 characters (approximately one paragraph). Representative examples of this response heterogeneity can be found in Figure A5. For the forwarded messages, 42.97% of firms in the C1B group received investor comments. The number of comments per firm ranged from one to 13, with a median of two comments. Comment length similarly varied, with a median of 14 Chinese characters (one concise sentence) and a standard deviation of 45 characters. Sections V.1, VI.1, and VII explore these patterns in depth.

IV.4 Empirical Specifications

This section outlines the specifications used in our analysis. Given that we collect data from a variety of sources, the data structure and corresponding regressions differ on a case-by-case basis. Here, we provide a brief overview of the primary methodologies, emphasizing the rationale behind our tests and the justifications for our causal estimates.

We start with firms' online responses using the following regression model:

$$Y_{ijrt} = \beta_0 + \beta_1 \times treat_r + \gamma X_r + \mu_i + \theta_{jt} + \varepsilon_{ijrt} \tag{1}$$

where i, j, r, and t represent firm, industry, question, and day, respectively. Y_{ijrt} captures the quality measures of firms' responses (e.g., length, number of ESG keywords, and sentiment) to questions on the Q&A platforms. $treat_r = 1$ if the question is part of our RCT. X_r includes question-level controls, such as question length and sentiment. μ_i represents firm-level fixed effects, controlling for time-invariant characteristics of each listed firm. θ_{jt} are industry-day fixed effects, accounting for time-varying events at the industry level, such as news shocks and industrial policies. ε_{ijrst} is the error term. Standard errors are clustered at the firm level.

The main coefficient of interest, β_1, captures the difference in response quality between our RCT questions and other similar questions to firms within the same industry on the same day. A positive β_1 suggests that firms provide higher-quality responses to our ESG questions compared to similar questions from other investors.

To investigate the causal impacts of our experiment on firm-level actions and market responses, we implement a difference-in-differences (DiD) design:

$$Y_{ijt} = \beta_0 + \beta_1 \times treat_i \times post_t + \mu_i + \theta_{jt} + \varepsilon_{ijt} \tag{2}$$

or

$$Y_{it} = \beta_0 + \beta_1 \times treat_i \times post_t + \mu_i + \varphi_t + \varepsilon_{it} \tag{3}$$

where i, j, and t represent firm, industry, and time, respectively. Y_{ijt} or Y_{it} are firms' outcome measures (such as release or quality of ESG reports, question or answer spillovers, question sentiments, and market price, each defined in subsequent sections). $treat_i = 1$ if the firm belongs to one of the RCT treatment arms. $post_t = 1$ after the experiment commences. μ_i are firm-level fixed effects, controlling for time-invariant characteristics of each listed firm. θ_{jt} are industry-day fixed effects, controlling for time-varying industry-level events. φ_t are quarter-level or year-level fixed effects, controlling for time-varying factors such as economic growth and stock market sentiments common to all the listed firms. ε_{ijst} is the error term. Standard errors are clustered at the firm level. Depending on the data structure, t may refer to day, quarter, or year. When data is at the day level (t refers to day), we use Equation (2) to incorporate firm-level and industry-by-day fixed effects. Otherwise, we implement Equation (3), replacing industry-day-level fixed effects with quarter-level or year-level fixed effects to allow for higher statistical power.

The coefficient of interest is β_1, which measures the difference in outcomes between treated firms and control firms after our experiment. Since the treatment status is randomly assigned regardless of any firm-level characteristics, we can interpret β_1 as the causal impact of our RCT on the outcome variable.

To further analyze the evolution of the treatment effects over time, we use a dynamic DiD approach on the same set of outcomes as in the DiD design and run the following regressions:

$$Y_{ijt} = \sum_{\tau=a,\tau\neq-1}^{b}(\alpha_\tau \times treat_i \times \mathbb{1}[t=\tau]) + \mu_i + \theta_{jt} + \varepsilon_{ijt} \tag{4}$$

or

$$Y_{it} = \sum_{\tau=a,\tau\neq-1}^{b}(\alpha_\tau \times treat_i \times \mathbb{1}[t=\tau]) + \mu_i + \varphi_t + \varepsilon_{it} \tag{5}$$

where i, j, and t represent firm, industry, and time, respectively. The only differences from Equations (2) and (3) are $\mathbb{1}[t=\tau]$, which is an indicator function that equals one when t falls in a time interval $\tau \in [a,b]$ around our experiment. We omit period $\tau = -1$ as the reference group. The coefficients of interest are a set of α_τ's, which measure the treatment effects of our experiment in each period. We expect α_τ $(\tau < 0)$ to be close to zero based on the randomization design and will test this parallel trend assumption for causal interpretation. Changes of α_τ $(\tau \geq 0)$ indicate the evolution of the causal effects of our experiment on the outcomes of interest.

Lastly, we investigate the heterogeneity of our treatment effect across groups. For daily data with rich variation, we employ the following regressions:

$$Y_{ijrst} = \beta_0 + \sum_{s=1}^{k}(\beta_{1s} \times treat_r \times Q_s) + \gamma X_r + \mu_i + \theta_{jt} + \rho_{st} + \varepsilon_{ijrst} \tag{6}$$

or

$$Y_{ijst} = \beta_0 + \sum_{s=1}^{k}(\beta_{1s} \times treat_i \times post_t \times Q_s) + \mu_i + \theta_{jt} + \rho_{st} + \varepsilon_{ijst} \tag{7}$$

or

$$Y_{ijst} = \beta_0 + \sum_{s=1}^{k}\sum_{\tau=a,\tau\neq-1}^{b} (\alpha_{\tau s} \times treat_i \times \mathbb{1}[t=\tau] \times Q_s) + \mu_i + \theta_{jt} + \rho_{st} + \varepsilon_{ijst} \tag{8}$$

which are revisions of Equations (1), (2), and (4) to incorporate group-wise estimates. Q_s refers to a dummy variable that equals one if firm i belongs to a group $s \in [1,k]$, and ρ_{st} refers to group-day fixed effects to control for time-varying common shocks within each group. For treatment and crosscut arms, group refer to T1/T2/T3/T4 or C1A/C1B, and we omit ρ_{st} in (7) and (8) as they would absorb the variation of interest. For productivity, transparency, leader traits, and cultural factors, groups correspond to the quartile a variable falls into prior to our experiment, thus

$k = 4$. For investor comments, the groups are defined by whether a firm is assigned to C1B and whether it has received any negative comments, resulting in $k = 3$ (only three possible combinations based on the RCT design).

The coefficients of interest are β_{1s} and $\alpha_{\tau s}$. They measure the treatment effects of our experiment on a specific group $s \in [1, k]$. The difference in estimates across s values help us identify the relative importance of treatment arms and the potential motivations behind firms' ESG responses and actions.

For quarterly or yearly data, we do not separate quartile groups due to insufficient statistical power. Instead, we introduce interaction terms with continuous variables of interest to examine heterogeneity. The revised regression models are as follows:

$$Y_{it} = \beta_0 + \beta_1 \times treat_i \times post_t + \beta_2 \times treat_i \times post_t \times K_i + \mu_i + \varphi_t + \varepsilon_{it} \quad (9)$$

or

$$Y_{it} = \sum_{\tau=a,\tau\neq-1}^{b} (\alpha_{\tau1} \times treat_i \times \mathbb{1}[t = \tau]) + \sum_{\tau=a,\tau\neq-1}^{b} (\alpha_{\tau2} \times treat_i \times \mathbb{1}[t = \tau] \times K_i) + \mu_i + \varphi_t + \varepsilon_{it} \quad (10)$$

which are revisions of Equations (3) and (5) to incorporate variation of treatment effects across firms. K_i represents a continuous variable—such as productivity or transparency measures—that is expected to explain potential heterogeneity in treatment effects. The coefficients of interest are β_2 and $\alpha_{\tau 2}$, which capture marginal treatment effects associated with firm-specific characteristics after controlling for the average treatment effects (β_1 and $\alpha_{\tau 1}$). Significant β_2 and $\alpha_{\tau 2}$ indicate that firms with certain characteristics are more or less responsive to the treatment than others. They also provide insights into which types of firms are driving the overall treatment effect.

V. How do Various Market Participants Respond to ESG Inquiries?

V.1 Online Responses

We begin by examining the responses we receive directly from management teams of listed companies. Figure 3 and Table A1 report average treatment effects across various dimensions of response quality, comparing experimental ESG-related questions (treatment group) with non-ESG questions matched on length and sentiment (control group). All specifications include firm and industry-day fixed effects to account for firm-specific and time-varying sectoral shocks.

The results reveal systematic differences in how firms address ESG inquiries relative to routine platform interactions. Treated responses are 21.2% longer and 16.3% more positive in sentiment than control responses, with a 29.4-fold increase in ESG keyword density. Firms disproportionately emphasize environmental disclosures—likely reflecting public salience of climate issues—while providing fewer governance-related details, consistent with the opacity of internal decision-making. Responses also adopt a more forward-looking tone, suggesting firms frame ESG as a long-term strategy. However, response specificity suffers: quantitative references and named entities are 38.8% and 36.7% less frequent than in control answers, potentially due to limited standardized metrics in this nascent domain. This ambiguity manifests in elevated boilerplate language, with treated responses containing 13.3% more generic phrasing. Notably, firms reduce mentions of accounting terms while increasing regulatory language, a pattern aligning with the non-financial, compliance-driven nature of ESG disclosures in emerging markets.[3]

Do firms perceive ESG engagement as reputationally valuable? Prior to our intervention, ESG discussions were exceptionally rare on these platforms. The novel visibility created by our experiment enables us to examine whether firms subsequently engage in voluntary amplification of ESG discourse. As Figure A8 demonstrates, treated firms begin proactively weaving ESG content into unrelated investor dialogues, such as pre-earnings announcement discussions, following exposure to our experiment. Panel A of Figure 4 quantifies this spillover using a dynamic DiD framework, tracking cumulative mentions of ESG keywords in responses to all platform questions after our experiment. Treated firms exhibit a sustained increase in ESG discourse relative to controls, with a statistically significant DiD estimate at the 5% level. While limited sample sizes preclude significance in individual periods, the persistent upward trajectory over six months post-intervention signals that firms perceive strategic value in ESG visibility.

Beyond firm responses, our analysis further reveals spillover effects in retail investors' ESG engagement. The public visibility of Q&A platforms allows participants to freely raise follow-up questions inspired by our interventions. Example in Figure A9 demonstrates this dynamic: investors expand discussions from corporate ESG ratings to partners' ESG performance for treated firms, while control firms face novel inquiries about ESG scrutiny during financing—a direct replication of our experimental critiques. Panel B of Figure 4 formalizes these patterns using a dynamic DiD design. The cumulative share of ESG questions shows parallel pre-trends, consistent with the historical absence of ESG discourse. Following the intervention, treated firms experience an immediate rise in ESG inquiries relative to controls, peaking after three months

[3] Appendix C demonstrates that firms' online responses show no evidence of (1) systematic answer replication across firms, (2) AI-generated content, (3) strategic targeting of experimental prompts, or (4) ESG-washing without accountability mechanisms. These checks address key endogeneity concerns, supporting the causal interpretation of our findings.

before moderating gradually. The DiD estimate indicates that treated firms' ESG question share nearly doubles the control mean (96.3% increase). This persistent investor scrutiny likely provides firms with extrinsic motivation to address ESG beyond regulatory compliance, complementing the intrinsic incentives of strategic reputation-building.

V.2 Offline Behaviors

Do firms translate heightened online ESG engagement into tangible real-world actions, or do they simply engage in symbolic communication to influence investor perceptions (Fioretti, 2022; Gibson Brandon et al., 2022)? We address this question by examining four dimensions of offline firm behavior. We begin by analyzing changes in ESG ratings, which are likely the most direct targets for firms since we reference these ratings in our questions. Next, we evaluate both the issuance and quality of ESG reports, which represent costly and verifiable commitments. Third, we monitor the prevalence of ESG-related discourse in institutional investor communications, interpreting it as strategic corporate investment in ESG visibility. Lastly, we provide suggestive evidence of differences in media coverage of ESG issues between treatment and control groups.

Figure 5 presents dynamic effect estimates from major ESG rating agencies in China. We exclude foreign agencies due to their limited coverage and lack of timely adjustments for Chinese firms. Panels A and B feature two widely cited rating agencies in our experiment. Since the probability of a specific agency being referenced in our messages is negatively correlated with pre-RCT ratings, this creates a selection-on-observables design where treatment assignment depends solely on observable rating outcomes. To address this selection, we incorporate propensity score matching (PSM) into the regressions to obtain causal estimates of the dynamic effect of our RCT, where the propensity to be treated (i.e., a message citing a specific agency) is predicted using the ESG rating from the same agency before our experiment. Panels C and D feature results from two uncited agencies, whose information became available only after our experiment concluded. For these agencies, we apply a standard dynamic DiD approach to identify causal effects.

Across the first four panels in Figure 5, we observe a positive trend in ESG ratings for treated firms compared to their control counterparts. The effect does not materialize immediately after the experiment, as it takes time for rating agencies to process new ESG information and adjust their ratings.[4] Importantly, the observed rating gains cannot be attributed to collusion between firms and agencies, as the pattern persists even for uncited agencies in Panels C and D. While

[4] Figure A10 demonstrates that the timing of these positive effects aligns well with each rating agency's adjustment schedule.

certain agencies (e.g., Wind and QuantData) incorporate online ESG discourse into their evaluations, the weight assigned to Q&A platforms appears marginal compared to substantive factors such as regulatory penalties or legal proceedings. This effectively rules out the possibility that our experimental questions serve as the main driver of rating changes. The consistent pattern across agencies further implies that firms enhance verifiable ESG practices detectable across diverse methodologies.

A crucial source of information for ESG ratings is the ESG/CSR reports. In Panel A of Figure 6, we investigate whether treated firms are more likely to release ESG reports following the public demand created by our experiment. Beyond the prevailing regulatory pressure on ESG disclosure that affects all firms uniformly, we observe a significantly positive DiD estimate of 2.8% for treated firms, which represents over 10% of the control mean. This suggests that randomly treated firms are significantly more likely to release an ESG report a few months after the public demand is initiated. Table A7 reveals that new reports exhibit quality comparable to pre-existing ones across readability measures and NLP-derived metrics (specificity, boilerplate, and dictionary-based keyword counts). These findings reject the hypothesis that firms prioritize low-effort "check-the-box" disclosures just for the sake of improving their ratings.

In addition to public ESG engagement with retail investors, firms may strategically emphasize ESG topics when meeting with institutional investors, who wield greater influence on corporate valuations. In Panel B of Figure 6, we perform a textual analysis of the transcripts from institutional investor communications and demonstrate a 1.95% increase in ESG mentions for treated firms, which nearly matches the control mean. As Table A8 details, this rise is predominantly driven by firms proactively introducing ESG topics rather than responding to investor inquiries.

Finally, we provide suggestive evidence on the trend of negative media reports on ESG issues for treated versus control firms. The last two panels of Figure 5 present the dynamic effects. Given the rarity of firm-specific ESG-related news (averaging 1.78 regulatory violations and 0.34 supply chain issues per firm during our sample period), we lack the statistical power to detect significant effects. However, for the two most frequent topic categories—regulation violations and supply chain issues—we observe a slight downward trend for treated firms. The most notable declines occur four months after the start of our experiment, coinciding with the period when companies typically publish annual reports and are under media scrutiny. Overall, the trend in media reports aligns with our findings from other offline actions, indicating that firms under public ESG pressure are inclined to undertake substantial efforts to enhance their ESG ratings.

V.3 Market's Responses

The combination of negative ESG scrutiny from our randomized inquiries and firms' proactive responses exerts competing pressures on valuations, raising the question of whether they yield a net market impact. In efficient markets, valuations should dynamically incorporate all available information, including both the reputational risks from our intervention and any subsequent ESG improvements. Because our randomized treatment assignment is orthogonal to concurrent market forces, we can isolate the causal effect of RCT-induced adjustments on stock performance free from confounding market trends.

Figure 7 traces the evolution of market prices for treated versus control firms. We detect no statistically or economically significant effect at any horizon, with differences consistently indistinguishable from zero. These findings indicate that market participants price the offsetting effects of negative ESG inquiries and positive corporate responses equally, resulting in no net valuation change.

Notably, despite standardized ESG inquiries, we observe pronounced heterogeneity in corporate responses across treatment arms and firm characteristics (see Figure A5 for examples). The aggregate null effect may thus arise from two distinct possibilities. First, consistent with Friedman's (1970) shareholder primacy view, financial markets may perceive ESG-related interactions as immaterial to fundamental value, leading investors to disregard both inquiries and responses. Second, the null effect could mask divergent valuation signals across ESG dimensions that net out in aggregation. Prior research indicates that E and S dimensions often entail external impacts on broader stakeholders, whereas G issues primarily reflect internal firm structures (Liang & Renneboog, 2017). These dimensions consequently differ in their financial materiality, measurement reliability, and stakeholder salience (Khan et al., 2016). Leveraging the unique feature of our experimental design, where treatment arms emphasize distinct E, S, or G dimensions, we next distinguish between these competing hypotheses. The following section examines whether firms, investors, and markets exhibit differential reactions across ESG pillars.

VI. How do Various Market Participants Respond to E/S/G-Specific Inquiries?

VI.1 Supply-Side Heterogeneity: Firms' E/S/G-Specific Responses

We start with examining supply-side heterogeneity in firms' responses, including both their online replies and offline actions. Figure 8 illustrates the variation in online response quality across treatment arms, benchmarked against non-experimental questions posed to the same firms on the same dates. Panel A reveals that generic ESG inquiries elicit responses disproportionately emphasizing environmental keywords over social and governance terms, suggesting firms possess greater familiarity with environmental issues relative to other dimensions. Turning to the dimension-focused treatments, E-focused messages generates twice the treatment effect of generic prompts in eliciting E-specific keywords, underscoring firms' ability to prioritize environmental concerns when explicitly prompted. Notably, even when queried about S or G dimensions, firms supply more dimension-specific information than unprompted pillars. These patterns suggest firms' capacity to distinguish ESG subtopics and tailor their disclosures to stakeholder priorities. Moreover, their responses reflect not only heightened public scrutiny but also the specific content of inquiries and the availability of relevant information.

Panel B of Figure 8 presents additional response quality metrics across treatment arms. Three key patterns emerge. First, generic ESG prompts yield the shortest, least positive, and least quantitative responses among treatment arms, indicating that dimension-specific queries are more effective in invoking information sharing. Second, E prompts produce the highest-quality responses across multiple metrics—length, keywords, sentiment, and quantitative detail—and are more forward-looking than responses to social or governance queries. This pattern reinforces firms' environmental competency demonstrated in Panel A. Third, G prompts generate responses richer in named entities, accounting terminology, and regulatory references—features consistent with governance's internal focus and alignment with conventional financial reporting. However, these responses also contain significantly more boilerplate language, suggesting either limited substantive action or strategic obfuscation in this domain.

In Table A11, we explore the heterogeneity of firms' follow-up actions across treatment arms. Mirroring patterns in online engagement, we find significant behavioral changes concentrated among firms receiving E prompts. Despite data limitations inherent to low-frequency outcomes, these firms exhibit the largest treatment effects: ESG ratings improve significantly for uncited agencies, ESG report issuance increases by 13.93% relative to the control mean, and ESG mentions during institutional investor interactions are 1.49 times higher than the control mean. While G treatment leads to occasional statistical significance, effect sizes are systematically smaller except for investor communications. Generic ESG prompts fail to induce measurable behavioral changes across outcomes. These results reinforce our earlier findings that listed firms prioritize environmental initiatives and demonstrate both greater responsiveness and implementation capacity for environmental versus social or governance dimensions.

VI.2 Demand-Side Heterogeneity: Investors' E/S/G-Specific Responses

How do investors perceive firms' heterogeneous ESG disclosures and subsequent actions? To examine this question, we employ a dynamic DiD framework to track shifts in both public interest and sentiment. Figure 9 exploits the differentiated focus of each treatment arm and disentangles dimension-specific treatment effects across ESG pillars.

Panel A compares the volume of ESG-related questions directed at treated versus control firms. Mirroring the trend of question spillovers in Figure 4, G messages drive the largest investor engagement, with treated firms receiving 1.55 times more ESG questions than the control mean. E and S messages also spur investor interest but with smaller relative increases (50% and 42.5%, respectively). These patterns suggest investors may perceive governance disclosures as insufficiently transparent, prompting follow-up scrutiny after initial corporate responses.

A sentimental analysis of investor questions in Panel B reinforces this narrative. G-treated firms experience an immediate and sustained decline in sentiment post-intervention, with negativity persisting for months and intensifying after the April 2024 annual report releases. This contrasts sharply with E message-treated firms, where sentiment stabilizes or even improves following proactive disclosures and tangible actions. S messages show no significant sentiment shifts, aligning with their intermediate investor engagement levels.

VI.3 Equilibrium: Stock Market's E/S/G-Specific Responses

How do supply- and demand-side heterogeneous ESG dynamics ultimately translate into market outcomes? Figure 10 examines price trajectories for firms receiving differently focused messages. Results reveal striking divergence: in the six months following the intervention, firms receiving E messages experience a significant 2.2% increase in market prices, firms receiving S messages see modest loss, but firms in the G message group face a clear downward trend (although statistically insignificant). These effects, though modest against market fluctuations (A-share indices varied between 9% and 30% over the same period), align qualitatively with documented impacts of reputation shocks and shareholder proposals (Akey et al., 2023; Flammer, 2015). Notably, in our setting, these effects emerge gradually rather than immediately after the experiment, suggesting that the market responds not merely to the initial intervention but to the cascade of subsequent real-world changes it incentivizes. For example, retail investors may have reduced holdings as they observe a rising number of governance-related inquiries over several months. Similarly, institutional investors may have adjusted valuations following delayed ESG rating updates or the release of annual ESG reports. Given the randomized design, firms receiving E, S, or G questions are balanced *ex-ante*, allowing us to attribute these dynamics to the ESG intervention rather than to concurrent market trends. In Appendix F, we further examine trends in alternative stock market performance measures, including market capitalization, cumulative log returns, and short-window cumulative abnormal returns (CAR), and find consistent results.

The heterogeneity across E, S, and G dimensions can be explained by earlier evidence of supply- and demand-side variation. On the supply side, E messages elicit higher-quality corporate responses, potentially enhancing brand reputation, whereas weaker responses to S and G messages may fail to offset the negative sentiment triggered by our queries, resulting in net valuation declines. On the demand side, persistent scrutiny of G issues amplifies valuation pressures, while proactive E engagement enhances corporate credibility. Although we cannot fully disentangle the underlying mechanism, the patterns are consistent with a signaling story under information asymmetry. High-quality firms can more credibly distinguish themselves through tangible, verifiable E actions. This differential verifiability is reflected in evidence that E ratings exhibit greater consensus across agencies than S or G ratings, as shown by Berg et al. (2022) and confirmed in our data (see Figure A11). G indicators, by contrast, are inherently less observable and harder to verify, limiting their usefulness for separating high- from low-quality firms. Consequently, investors may interpret G-related inquiries as signals of unresolved agency problems or structural weaknesses, while viewing E actions as more credible signals of overall firm quality and management competence.

Taken together, these results highlight asymmetric market perceptions of ESG dimensions in China. Firms demonstrate greater responsiveness to E pressures, likely due to clearer metrics and stakeholder salience. Retail investors, in turn, reward E transparency but penalize G disclosures, which they may associate with unresolved agency problems or regulatory vulnerabilities. In equilibrium, market valuation reflects a dynamic evaluation process that weighs both the timeliness of corporate communications and the credibility of their subsequent actions.

VII. Examining the Motives behind Firms' ESG Actions

To rationalize our findings and guide the heterogeneity analysis, we develop an illustrative signaling model, with formal derivations provided in Appendix G. Building on Spence's (1973) classical framework, the model formalizes our central argument: firms undertake costly ESG actions to credibly signal their underlying quality (e.g., productivity) in markets with information asymmetry.

The key intuition is that high-quality firms—those with greater resources and capabilities—can engage in ESG initiatives at a lower marginal cost than low-quality firms. This "sorting condition" allows costly ESG actions, such as publishing detailed reports or making new environmental commitments, to function as a credible signal of a firm's hidden quality. This simple framework generates several testable predictions about which firms are most likely to engage in ESG signaling. Specifically, the model predicts that the equilibrium level of ESG signaling will be higher for firms that are (1) more productive, (2) less transparent (i.e., face greater information asymmetry), and (3) have a larger base of ESG-conscious investors.

We now turn to the data to evaluate these predictions. We consider both firms' online responses and offline actions as ESG signals and test the comparative statics implied by the model. Additionally, we utilize market price data to examine whether investors reward these signals in a manner consistent with the theoretical corollary.

VII.1 Firm Productivity and ESG Responses/Actions

We first test proposition 1: whether firms with higher productivity are more willing to send ESG signals. Because productivity is not directly observable, we rely on imperfectly measured proxies to infer the relationship. In Panel A of Figure A13, we utilize four different variables: ROA, ROE, and two TFP measures based on firms' value added and revenue to approximate firms' inherent potential to earn profit (see Appendix H for methodological details). Notably, these four measures exhibit weak correlations, with pairwise correlations below 0.35. This indicates a lack of market consensus regarding firms' productivity, with each proxy capturing only a specific aspect.

Panel A of Figure 11 presents results from Equation (6). Consistent with Proposition 1, the findings suggest that firms with higher productivity are more willing to supply higher-quality responses to our ESG questions. This result holds across different measures of firm productivity and response quality. The effect is most pronounced in the highest-productivity group, which theoretically has the most capable personnel and abundant resources to invest in ESG actions.

Do high-productivity firms translate their stronger ESG signals into concrete actions? In Table A15, we examine the heterogeneity of their offline ESG actions in terms of ESG ratings, publication of ESG reports, mentions of ESG to institutional investors, and negative media reports. For the first three measures, higher values indicate better ESG performance, and we find that the interaction term between the DiD estimator and ROA (a proxy for productivity) is significantly positive in most cases. For negative media reports, lower values indicate fewer ESG scandals/incidents, and we find significantly negative interaction coefficients as predicted by the model. In summary, firms do act on their ESG commitments. High-productivity firms that send the strongest signals are observed to improve their ESG performance to the greatest extent.

VII.2 Firm Transparency and ESG Responses/Actions

We then move on to test Proposition 2, which examines the relationship between a firm's inherent transparency and its ESG signaling behavior. The literature has put forward a number of measures of firm transparency, such as ownership structure, board composition, rating divergence, and the number of external analysts (Armstrong et al., 2014; Avramov et al., 2022; Boone & White, 2015). To avoid relying on a single indicator, we collect data on a variety of measures and standardize them to construct a set of transparency indices. The summary index is comprised of three sub-indices, including the internal management transparency index, the external relationship transparency index, and the market research transparency index, each consisting of four well-documented transparency indicators (see Appendix I for details). Similar to productivity measures, the transparency sub-indices exhibit low pairwise correlations (Panel B of Figure A13), suggesting they capture distinct dimensions of information asymmetry.

In Panel B of Figure 11, we present the heterogeneity of firms' response quality across the four transparency indices.[5] The results consistently show that lower-transparency firms are more eager to send high-quality ESG signals, possibly due to their lack of communication channels in the financial market. Only firms with below-median transparency supply significantly higher-quality responses to our ESG questions, whereas firms with above-median transparency respond to ESG questions similarly to other types of questions on the platforms. This is consistent with Proposition 2, which suggests that higher-transparency firms do not need to engage in costly signaling, given the high market consensus on their productivity and quality.

In Table A17, we further investigate whether these less transparent firms take more ESG actions than their higher transparent counterparts. The results support our hypothesis. Columns 1-6 indicate that low-transparency firms make greater efforts to improve ESG ratings, release ESG reports, and advertise ESG during investor communications. Columns 7-8 suggest that these firms receive fewer negative media reports on ESG topics. Notably, we document an economically negligible correlation between transparency and productivity (coefficient of -0.044 for ROA and transparency index). As shown in Figure A15, the transparency heterogeneity results remain robust to the inclusion of productivity measures in the regressions. This suggests that transparency serves as a distinct driver of firms' ESG actions, operating independently of firm productivity.

[5] While we focus on the heterogeneity across these indices in the main text, results separate for different indicators are included in Figure A14.

VII.3 Investor Preferences and ESG Responses/Actions

Proposition 3 suggests that firms with more ESG-conscious investor bases have greater incentives to send signals to uninformed investors. In the context of China, retail investors play a dominant role in stock trading and market fluctuations. Therefore, their ESG perceptions likely shape corporate signaling decisions. Our experiment explicitly tests this channel by disseminating 40% of our platform questions to stock forums and social media, where retail investors actively discuss firms' stock market performance. We maintain a neutral tone and use diverse phrases to encourage genuine interactions with retail investors. We then analyze whether retail investors' ESG-related sentiment in these forums elicits differential responses from treated firms.

Unfortunately, among the 1,180 firms in the forward crosscut group, only 507 (42.97%) received any responses from retail investors. This lack of response was not only due to limited attention from retail investors but also various censorship issues on public forums, such as posting frequency limits and traffic control by administrators. Several of our posts were hidden or removed after a few days, restricting their influence and limiting potential interactions. Nevertheless, we received a total of 1,100 comments from retail investors, averaging two comments per firm. The comment length had a median of 14 Chinese characters (one short sentence) and a large standard deviation of 45 characters. We calculated the sentiment of these comments for each firm as a proxy for the ESG consciousness of their investor base.

Since ESG is still a relatively new concept in China, most retail investors show little knowledge or interest in the topic. They overwhelmingly treated our questions as irrelevant to the stock market, posting negative or toxic comments (see Figure A16 for examples). Among firms exposed to investor feedback, 61.74% received at least one negative comment. The remainder received only positive or neutral comments, which may not discourage them from sending ESG signals.

We are interested in comparing firms' signaling behavior in response to investor sentiments, conditional on their exposure to investor attention. Therefore, we restrict our treatment group to the 1,180 firms to which we forwarded Q&A messages. We then examine the differences in coefficients between firms that received no negative comments and those that received at least one negative comment. Panel C of Figure 11 presents the regression estimates. Across three measures of firm response quality, we find that firms that did not receive any negative comments from retail investors tend to provide higher-quality and more positive answers to our ESG inquiries. This indicates that firms value retail investors' opinions and strategically adjust their signaling behavior on public communication channels, in line with Proposition 3.

VII.4 Market Returns to ESG Responses/Actions

In our signaling framework, firms engage in ESG activities primarily to secure positive market valuation from imperfectly informed investors. Should markets exhibit inefficiency or sluggish price adjustments, firms would lack incentives to invest in costly signaling. We empirically test this feedback mechanism using daily market price data.

According to our corollary, investors' aggregate market valuation should be positively correlated with firms' signaling efforts as long as there exist ESG-conscious investors. Integrating this corollary with our three validated propositions, we hypothesize that high-productivity, low-transparency firms and those facing fewer negative investor comments will reap greater valuation benefits following their signaling behaviors. Table A19 supports this prediction. Beyond the average treatment effect term $treat_i \times post_t$, we introduce interaction terms with ROA, the transparency index, and negative comment indicators to investigate the heterogeneous treatment effects across various motivation factors. We find that market responses align with signaling intensity: firms undertaking more proactive ESG actions garner larger valuation gains.

To further disentangle which signal dimensions investors value, we decompose market returns into two components: (1) marginal returns for above-median response quality (proxied by reply length) and (2) marginal returns for ESG improvements across dimensions. As shown in Table A20, both components show positive, largely significant valuation contributions, indicating investors reward both high-quality ESG engagement and substantive improvements. While we do not claim a causal interpretation of these results, the consistency across firms' online responses, offline actions, and market reactions all appear to align with the predictions of the signaling model.

VII.5 Alternative Hypotheses

Since Starks (2023), the value-versus-values debate over investor and manager motivations for ESG has gained tremendous popularity. Our signaling framework largely aligns with value motivation, where firms invest in ESG in pursuit of profit maximization. However, a plausible alternative hypothesis suggests that firms' ESG decision-making may be driven by nonpecuniary preferences, leading them to sacrifice some profit in exchange for social well-being.

The literature has proposed several preference-based factors that could shape firms' ESG decisions, which generally fall into two categories: leader traits and locational factors. The first category includes attributes such as leaders' education, joint appointments in academia, gender, and government connections (Borghesi et al., 2014; McGuinness et al., 2017). For instance, a highly educated female leader with academic and government connections may be more inclined to conform to social norms even without explicit requirements. The second category includes cultural and customary factors that influence firms' operations within the socio-economic environment (Cai et al., 2016; Wang & Juslin, 2009). For example, regions influenced by historical collectivism or Confucianism may be more inclined to pursue social goals alongside corporate profits. We empirically test both sets of values motivations using well-documented variables in the literature.

In Figure 12, we present the heterogeneity of firms' responses across leader and cultural factors. Panel A focuses on leader traits, where leaders are defined as chairpersons, vice-chairpersons, CEO, and Vice-CEOs who are equivalent to "C-suite" executives at American firms (Fisman & Wang, 2015). We examine variation across four dimensions: (1) average educational attainment, (2) academic affiliations, (3) proportion of female leaders, and (4) share of leaders with prior government experience (see Appendix J for details). Panel B investigates location-based cultural factors using four historical proxies: (1) Jinshi density (highest imperial examination rank) as a measure of human capital accumulation, (2) Confucian clan density capturing collectivist norms, (3) distance to the nearest Zhu Xi academy reflecting knowledge networks, and (4) genealogy book counts indicating social cohesion. The highlighted groups represent those theoretically most likely to invest in ESG based on values-driven motivations. However, we find no systematic patterns across quartiles that align with theoretical predictions for any of these measures. This null result stands in sharp contrast to the strong relationships observed with productivity and transparency measures, suggesting values may play a limited role in explaining firms' ESG engagement decisions. In Figure A17, we present complementary results using headquarters locations to define the heterogeneities; again, we find no systematic patterns.

VIII. Conclusion

This study provides a comprehensive examination of the demand-supply dynamics in corporate ESG actions within China. Utilizing a nationwide experiment conducted on online Q&A platforms established by stock exchanges, we create exogenous ESG demand shocks to firm management teams and collect a comprehensive dataset to trace the subsequent impact-generating process. Additionally, we formulate and empirically test a signaling model to explain the underlying motives behind firms' ESG actions.

We find that treated firms actively address ESG concerns and are willing to invest in concrete actions to meet public demand. The experiment effectively triggered voluntary information sharing about firms' ESG commitments and prompted treated firms to undertake costly measures to improve their ESG ratings, publish ESG reports, and advertise their ESG efforts. These investments garnered a positive market response: treated firms experienced fewer negative media reports, which translated into better stock performance. Notably, investors exhibit distinct perceptions of the E, S, and G dimensions, generally viewing environmental issues positively, social issues neutrally, and governance issues negatively. This perception is reflected in diverging market trends across treatment groups following the experiment.

To further understand the motivations behind firms' ESG decisions, we conceptualize their behavior through an illustrative signaling model. Consistent with model predictions, we find robust evidence that firms invest in ESG for potential market value gains, rather than being driven by values-based motivations to achieve social goals at the expense of corporate profits. This insight offers policymakers a refined perspective for designing regulatory frameworks and market incentives that harness firms' profit-driven motives to promote sustainable corporate practices. Likewise, investors can better tailor their strategies by recognizing how different ESG facets influence firm valuation and behavior.

Our information intervention sets an example of how individual voices can catalyze social change. We show that public communication channels significantly stimulate corporate ESG responses, challenging the conventional collective action problem and complementing the top-down regulatory approach. When individuals voice concerns and engage in online discussions, they generate demand for greater ESG transparency and accountability, compelling companies to take proactive steps to enhance their ESG performance. These voices also act as a critical information channel, informing firms of social preferences and potential market payoffs.

Looking ahead, our study opens several avenues for future research. While our intervention demonstrates the power of "soft" information shocks, an important next step is to explore how firms respond to "harder" forms of pressure, such as coordinated shareholder proposals or the threat of divestment. Furthermore, our research focuses on the market's perception of ESG actions as signals; future work could link these signals to tangible real effects, such as examining whether firms that signal environmental commitment subsequently reduce their actual pollution levels, perhaps by using satellite or administrative data. Finally, understanding the fundamental drivers of heterogeneous stakeholder demand for ESG remains a critical frontier. Exploring how social norms, media narratives, and peer effects shape the ESG preferences that firms respond to would provide a more complete picture of the pro-social market equilibrium.

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Tables and Figures

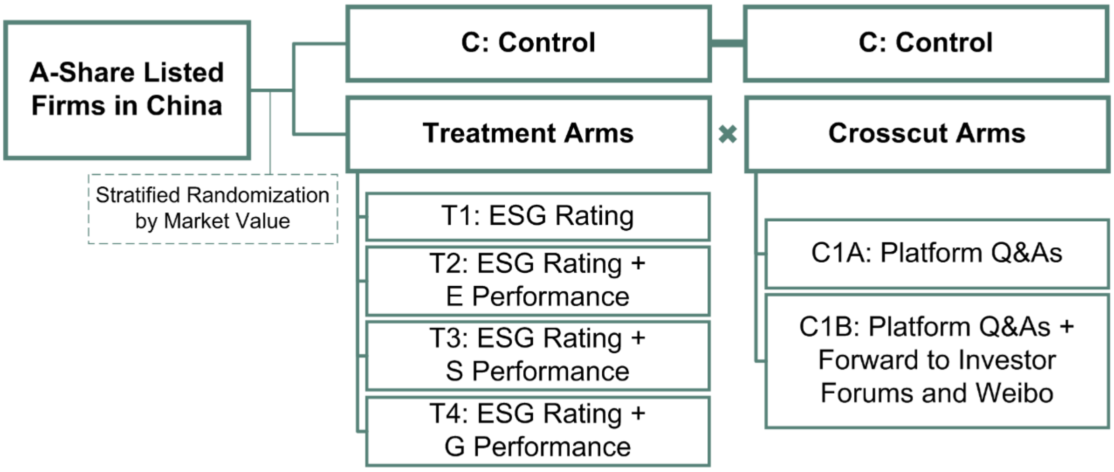


Figure 1. Experimental Design

Notes: This figure outlines our experimental design. For all the non-financial listed firms in China with at least one active question on either Q&A platform in 2023, we apply the stratified randomization method to assign them either to the control arm (40% of the sample) or one of the treatment arms (each 15% of the sample). Within the treated firms, we further randomize them independently into one of the crosscut arms (60% C1A and 40% C1B).

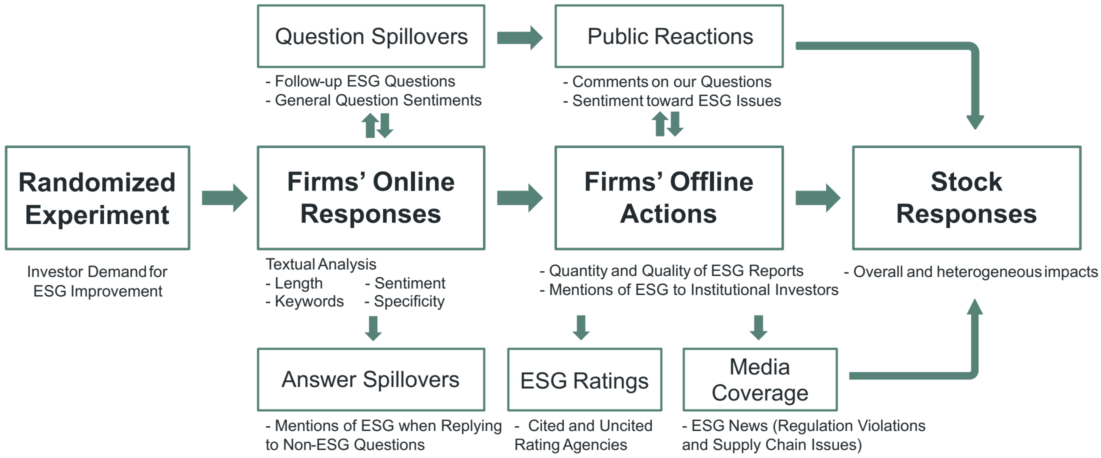


Figure 2. Impact-Generating Process

Notes: This figure plots the impact-generating process we trace in this study. The central row captures focal firm-level responses: (1) online answers to our experimental questions, (2) subsequent offline ESG improvements, and (3) market valuation changes. These constitute our primary outcomes of interest. The top row documents spillover effects on other market participants, including follow-up investor questions on Q&A platforms and public discussions on stock forums/social media. The bottom row tracks broader ESG engagement, encompassing voluntary ESG disclosures on other platform topics and third-party evaluations by rating agencies/media. Arrows indicate the temporal sequence of post-experiment events.

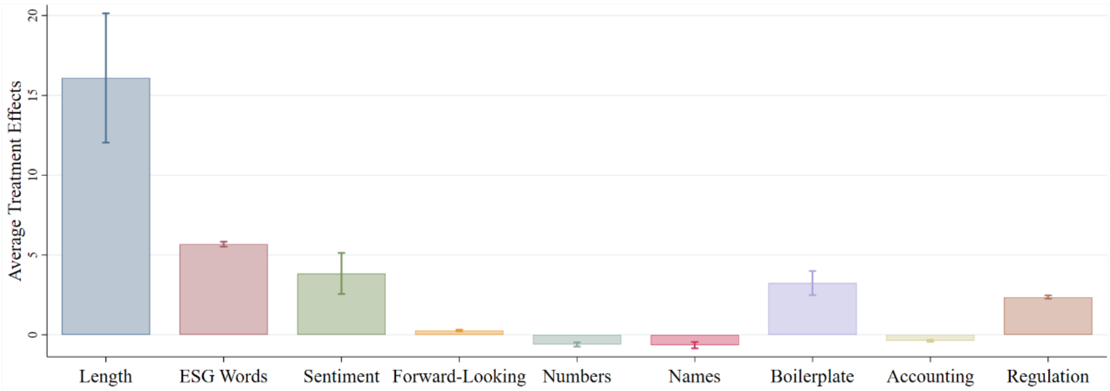


Figure 3. Firms' Aggregate Online Responses

Notes: This figure presents the aggregate treatment effect estimates of our experiment on firms' online responses on Q&A platforms based on Equation (1). The dependent variables include four categories of response quality metrics. The first category comprises basic textual features, including response length (measured by the number of Chinese characters), ESG keyword counts, and answer sentiment. The second category, numbers and names, quantifies the density of quantitative information (dates, times, ordinals, cardinals, quantities, percentages, and monetary values) and named entities (organizations, products, locaterions, and persons) identified using SpaCy's Named Entity Recognition (NER) tool (Lin et al., 2024), normalized by total word count. The third category measures boilerplate language, defined as the proportion of generic words detected using phrase-matching methods from Lang and Stice-Lawrence (2015). The final category evaluates thematic content, including forward-looking, accounting, and regulatory language shares, calculated via normalized counts of dictionary terms from Bozanic et al. (2018) and Muslu et al. (2015). The independent variable is a binary indicator for whether a specific question belongs to one of our treatment arms. Each bar represents a regression estimate, with error bars indicating 95% confidence intervals. All regressions control for question length and sentiment and include firm and industry-by-day fixed effects. Standard errors are clustered at the firm level to address potential serial correlation. The corresponding regression estimates are reported in Table A1.

Panel A: Answer Spillovers

Panel B: Question Spillovers

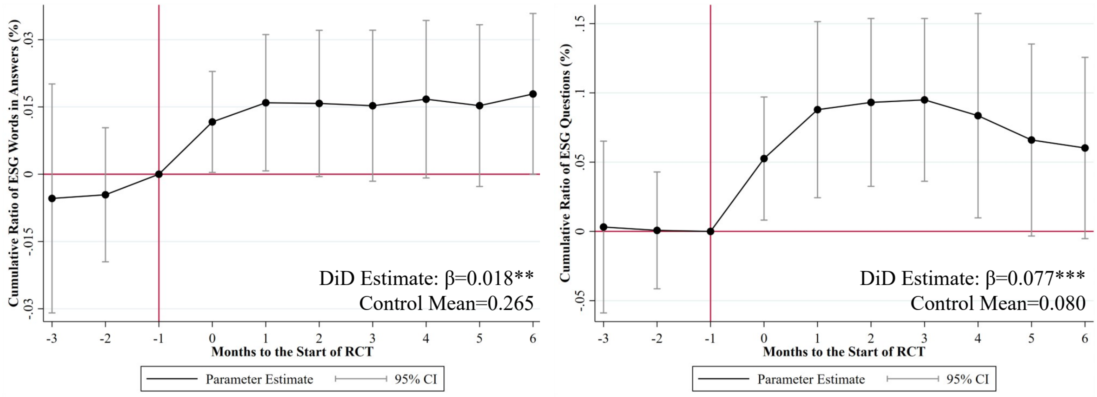


Figure 4. Firms' Answer Spillovers and Investors' Question Spillovers

Notes: This figure presents the estimates of dynamic treatment effects on ESG-related spillover behavior, estimated using Equation (4). Panel A examines firms' response patterns, where the dependent variable is the cumulative ratio of ESG keywords in firms' answers to total words across all responses. This measure captures the relative emphasis placed on ESG topics by treated versus control firms. Panel B analyzes investor behavior, with the dependent variable defined as the cumulative ratio of ESG-related questions directed at treated versus control firms, reflecting heightened investor interest following our intervention. The independent variables in both specifications are the interaction terms between period and treat dummies to measure the period-specific treatment effect. Dots represent regression estimates, and error bars indicate 95% confidence intervals. Standard errors are clustered at the firm level to address potential serial correlation. The corresponding regression estimates are reported in Table A5.

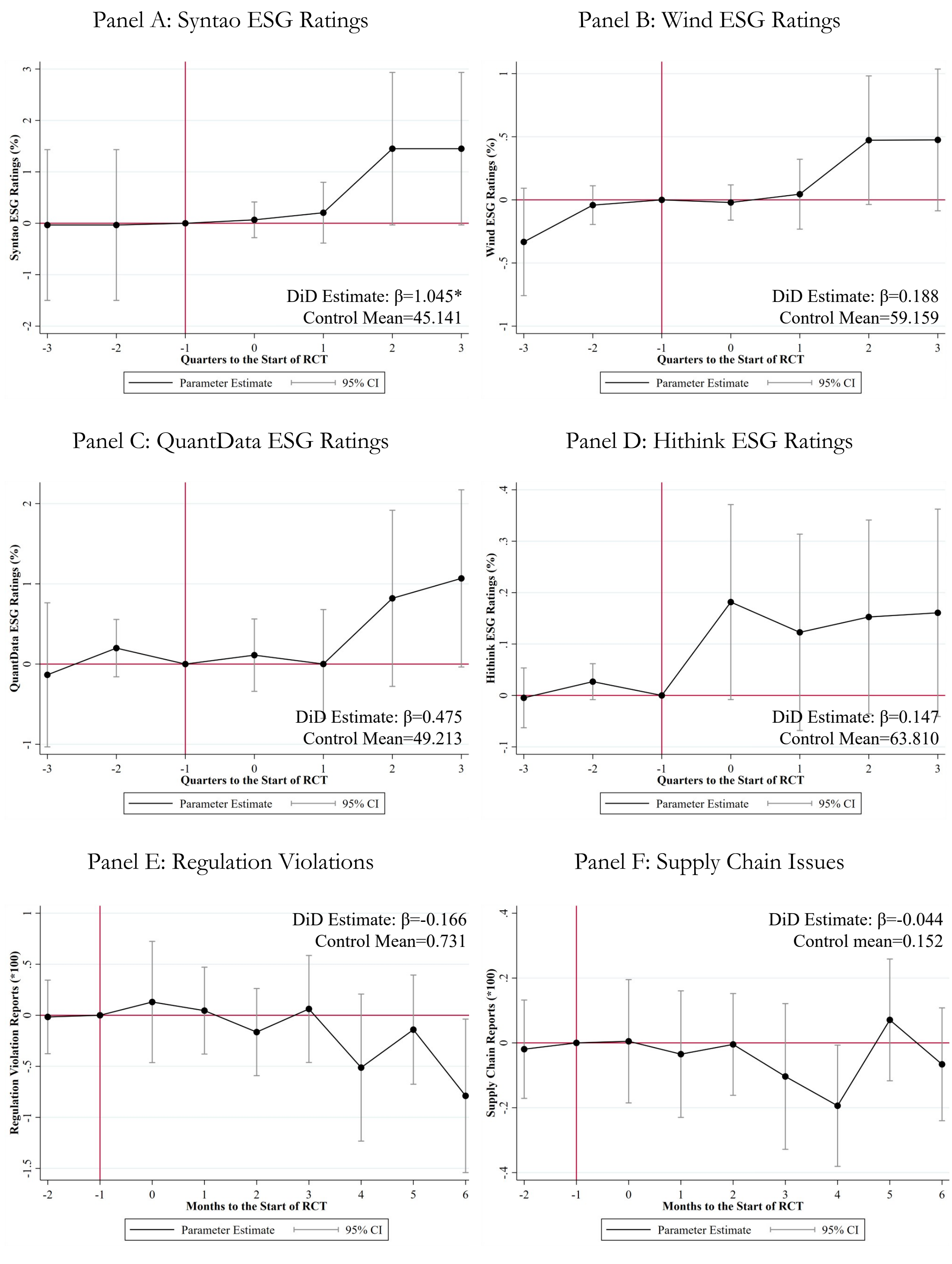


Figure 5. Impacts on ESG Ratings and Media Coverage

Notes: This figure presents the estimates of dynamic treatment effects on ESG ratings and media coverage. Panels A and B analyze two rating agencies frequently cited in our experimental messages, controlling for propensity scores in Equation (5) to address selection bias in rating results. Panels C and D examine uncited agencies using a standard dynamic DiD design based on Equation (5). For media coverage, Panels E and F track the two most prevalent ESG-related news topics, regulatory violations and supply chain issues, estimated via Equation (4). The key independent variables in all specifications are the interactions between period and treat dummies to measure the period-specific treatment effect. Dots represent regression estimates, and error bars indicate 95% confidence intervals. Standard errors are clustered at the firm level to address potential serial correlation. The corresponding regression estimates are reported in Table A6.

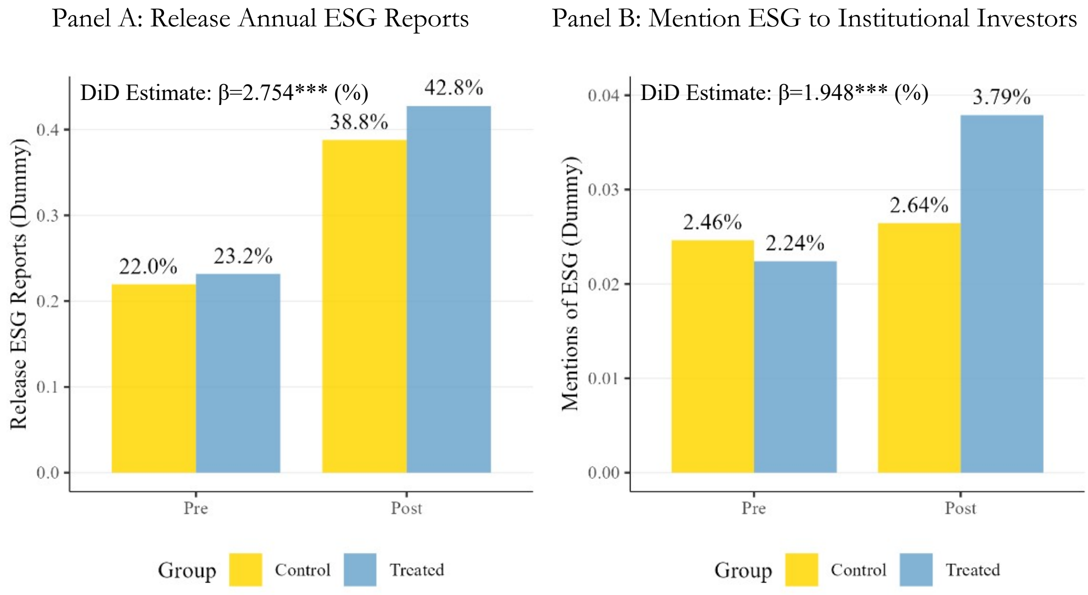


Figure 6. Impacts on ESG Reports and Institutional Investors

Notes: This figure compares treated and control firms' ESG disclosure behaviors before and after the experiment. Panel A presents the proportion of firms releasing ESG reports, while Panel B shows the frequency of ESG mentions during institutional investor interactions (site visits, calls, or interviews). Yellow bars represent control group means; blue bars represent treatment group means. For ESG reports (Panel A), each firm has one observation in the post-period (2023 reports released in 2024) and multiple observations in the pre-period (2017-2022 reports). For investor interactions (Panel B), we calculate the ratio of events containing explicit ESG discussions based on transcripts. DiD estimates are presented at the top left corner with statistical significance *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. The corresponding regression estimates are reported in Table A6.

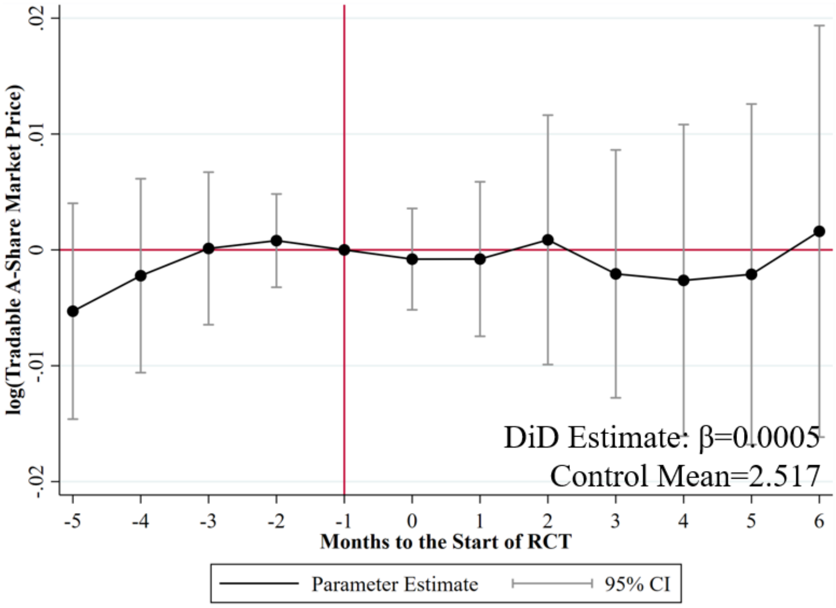
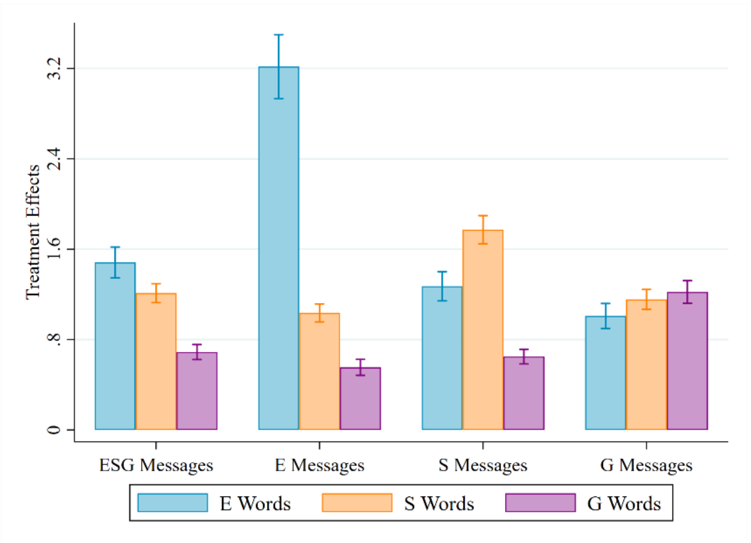


Figure 7. Aggregate Market Responses

Notes: The figure presents the estimates of dynamic treatment effects on firm market prices, estimated using Equation (4). The dependent variable is the natural logarithm of daily tradable A-share closing prices at the firm level. The independent variables are the interaction terms between period and treat dummies to measure the period-specific treatment effect. Dots represent regression estimates, and error bars indicate 95% confidence intervals. Standard errors are clustered at the firm level to address potential serial correlation. The corresponding regression estimates are reported in Table A9.

Panel A: ESG Keywords



Panel B: Other Quality Measures

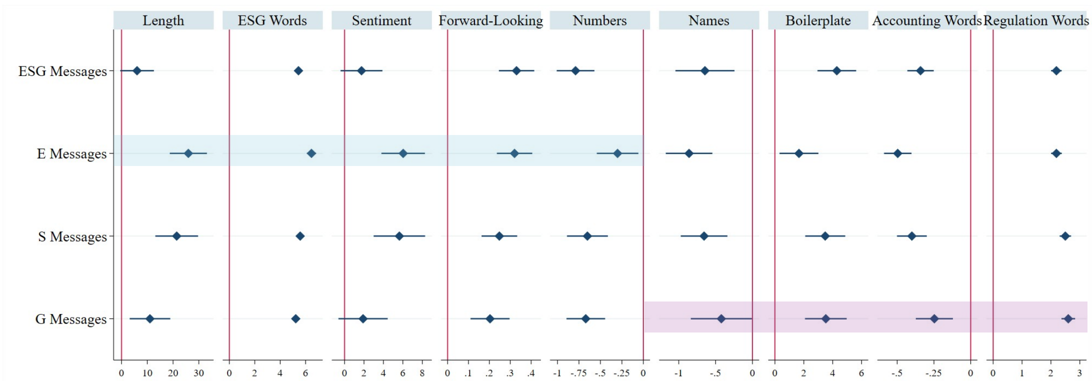


Figure 8. Firms' Responses to E/S/G-Specific Inquiries

Notes: This figure estimates heterogeneous treatment effects across experimental arms on firms' online response quality using Equation (6). Panel A displays treatment effects on ESG keyword usage, with the x-axis indicating treatment arms and the y-axis showing coefficient estimates for ESG keyword counts in responses. Panel B presents effects on four categories of response quality metrics. The first category comprises basic textual features, including response length (measured by the number of Chinese characters), ESG keyword counts, and answer sentiment. The second category, numbers and names, quantifies the density of quantitative information (dates, times, ordinals, cardinals, quantities, percentages, and monetary values) and named entities (organizations, products, locations, and persons) identified using SpaCy's Named Entity Recognition (NER) tool (Lin et al., 2024), normalized by total word count. The third category measures boilerplate language, defined as the proportion of generic sentences detected using phrase-matching methods from Lang and Stice-Lawrence (2015). The final category evaluates thematic content, including forward-looking, accounting, and regulatory language shares, calculated via normalized counts of dictionary terms from Bozanic et al. (2018) and Muslu et al. (2015). The independent variables are dummies indicating whether a question belongs to each of our treatment arms to capture group-specific average treatment effects. All regressions control for question length and sentiment and include firm and industry-by-day fixed effects. Points represent coefficient estimates, with error bars denoting 95% confidence intervals. Highlighted estimates indicate treatment arms with the largest effects. The corresponding regression estimates are reported in Table A10.

Panel A: ESG Question Spillovers

Panel B: General Question Sentiments

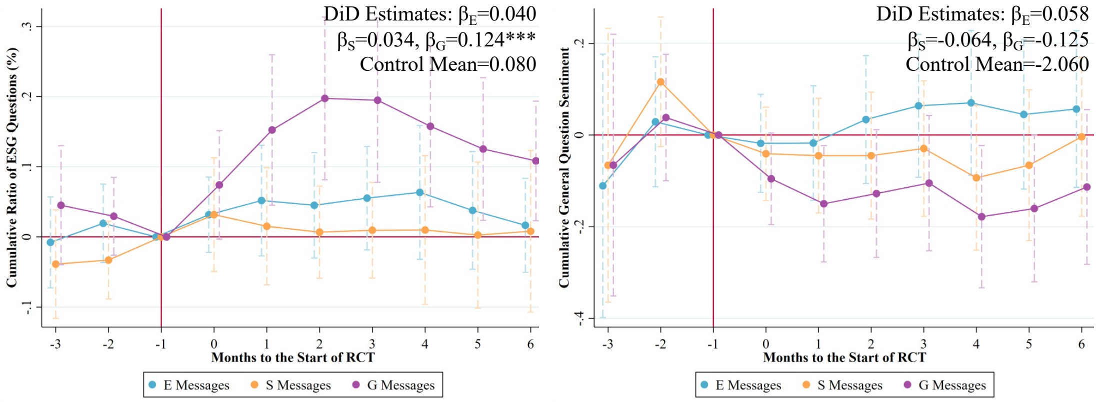


Figure 9. Investors' Responses to E/S/G-Specific Inquiries

Notes: This figure presents treatment effect heterogeneity in investor engagement across experimental arms, estimated using Equation (8). Panel A analyzes the cumulative count of ESG-related follow-up questions, while Panel B tracks the cumulative average sentiment score of all investor inquiries on the platforms since the start of the data collection period. The independent variables are the interaction terms between period and treatment arm dummies to measure the period- and group-specific treatment effect. Dots represent regression estimates, and error bars indicate 95% confidence intervals. Standard errors are clustered at the firm level to address potential serial correlation. The corresponding regression estimates are reported in Table A12.

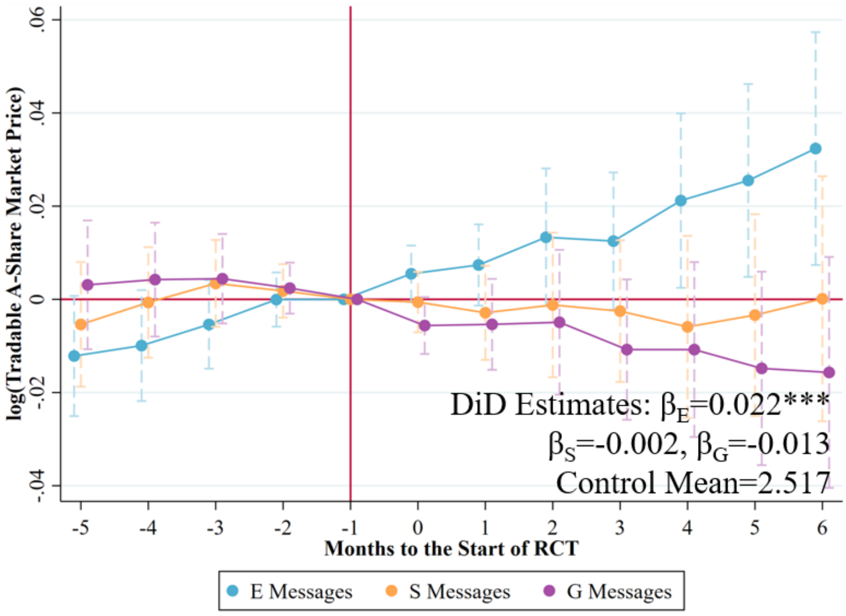
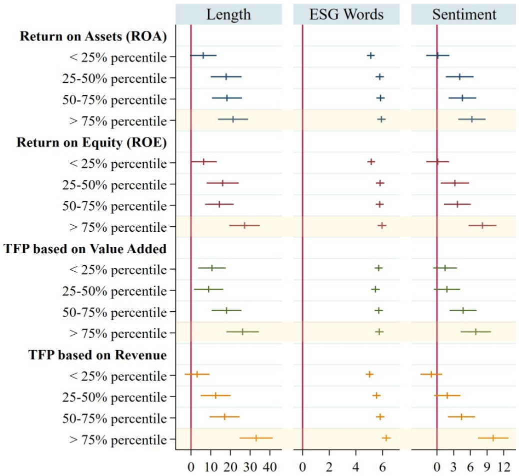


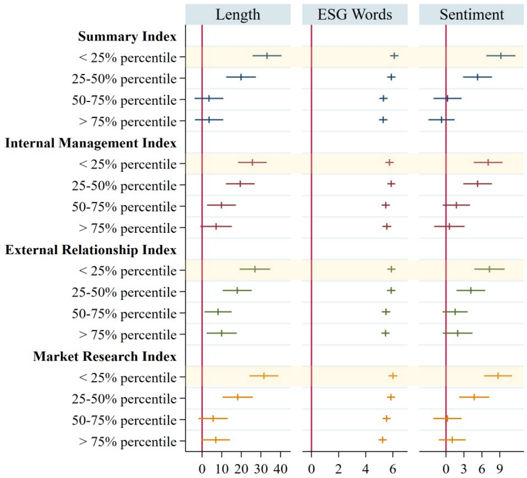
Figure 10. Market Responses to E/S/G-Specific Inquiries

Notes: This figure presents treatment effect heterogeneity in stock market responses across experimental arms, estimated using Equation (8). The dependent variable is the natural logarithm of daily tradable A-share closing prices at the firm level. The independent variables are the interaction terms between period and treatment arm dummies to measure the period- and group-specific treatment effect. Dots represent regression estimates, and error bars indicate 95% confidence intervals. Standard errors are clustered at the firm level to address potential serial correlation. The corresponding regression estimates are reported in Table A9.

Panel A: Heterogeneity Across Productivity Measures



Panel B: Heterogeneity Across Transparency Measures



Panel C: Heterogeneity Across Investor Preferences

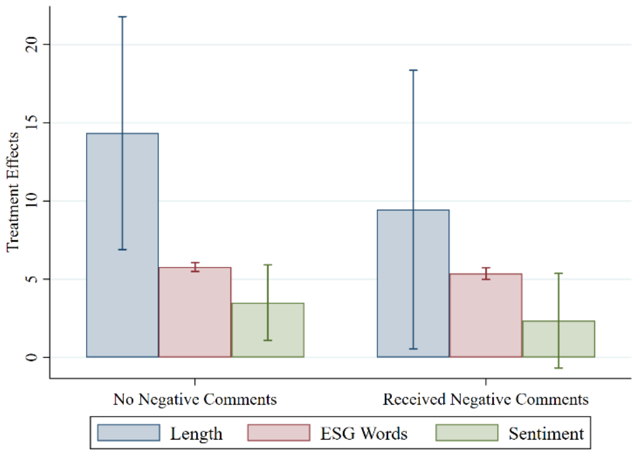


Figure 11. Firms' Responses Vary by Productivity, Transparency, and Investor Preference

Notes: This figure analyzes how firms' online response quality varies across three dimensions: productivity (Panel A), transparency (Panel B), and investor preferences (Panel C), estimated via Equation (6). We measure response quality through three metrics: (1) answer length (the number of Chinese characters), (2) the number of ESG keywords in answers, and (3) sentiment scores from textual analysis. Panels A and B group firms into quartiles based on their continuous productivity and transparency measures. Panel C distinguishes between C1B-group firms that received negative investor comments and those that did not. Each dot or bar represents a regression estimate, with error bars denoting 95% confidence intervals. The highlighted quartile groups are those expected to exhibit the largest effects according to our conceptual framework. The corresponding regression estimates are reported in Table A14, Table A16, and Table A18.

Panel A: Leader Traits

Panel B: Cultural Factors

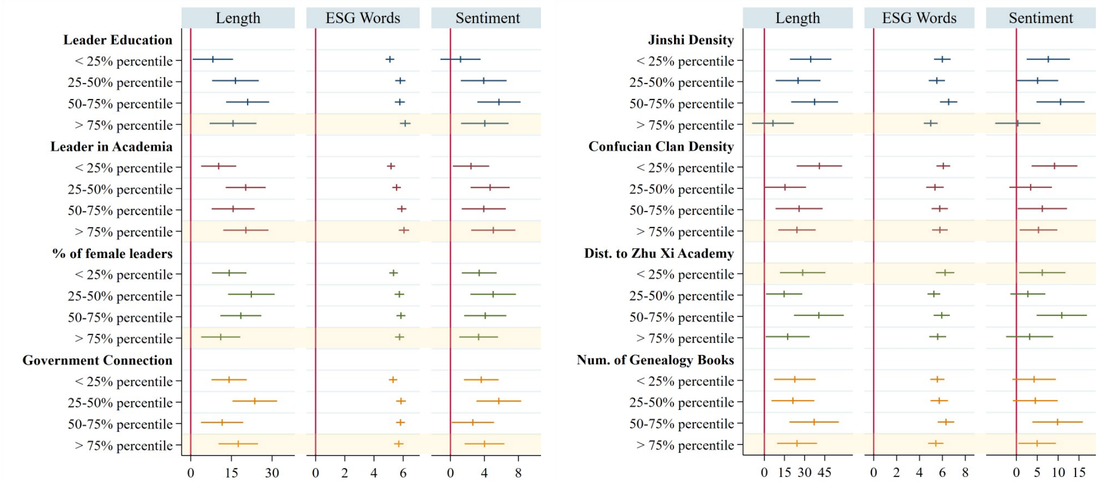


Figure 12. Firms' Responses DO NOT Vary by Leader Trait or Cultural Factor

Notes: This figure analyzes how firms' online response quality varies across leader traits and cultural factors (values-based motivations), estimated via Equation (6). All indicators are continuous and divided into four quartiles. Each dot represents a regression estimate, with error bars indicating 95% confidence intervals. The highlighted quartile groups are those expected to exhibit the largest effects according to values-driven motivations. The corresponding regression estimates are reported in Table A21 and Table A22.

Table 1. Summary Statistics (Jan-Nov 2023, Pre-Experiment)

Platform	Shenzhen (SZ)				Shanghai (SH)			
Panel A: Firm-Level Statistics	Mean	Sd	Min	Max	Mean	Sd	Min	Max
Number of Firms	2,753				2,099			
Number of Questions Per Firm	105	109	1	1,270	51	96	1	3,587
Number of ESG Questions (Broadly-Defined)	5	9	0	132	3	5	0	123
Number of ESG Questions (Narrowly-Defined)	0	0	0	4	0	0	0	6
Reply Rate	93%	17%	0%	100%	82%	27%	0%	100%
Reply Time (Days)	9	16	0	281	14	18	0	210
Reply Length (Characters)	94	45	17	515	111	54	12	629
Panel B: Topic Distribution	Count		Ratio		Count		Ratio	
Number of Questions	287,356				106,320			
Operation	168,430		58.61%		54,370		51.14%	
Financial Management	52,117		18.14%		22,139		20.82%	
Stock Trading	39,953		13.90%		16,935		15.93%	
External Market or Regulation	10,965		3.82%		4,145		3.90%	
Broadly-Defined ESG	14,228		4.95%		7,883		7.41%	
- Environment (E)	3,398		1.18%		1,045		0.98%	
- Social (S)	2,687		0.94%		1,448		1.36%	
- Governance (G)	8,031		2.79%		5,297		4.98%	
- Narrowly-Defined ESG	112		0.04%		93		0.09%	
- ESG Ratings	2		0.00%		5		0.00%	
- Other ESG Topics	110		0.04%		88		0.08%	
Other Questions	1,663		0.58%		848		0.80%	

Notes: This table presents the summary statistics of the Shenzhen and Shanghai Q&A platforms prior to our experiment. Panel A presents firm-level statistics. Narrowly-defined ESG questions refer to those that explicitly reference keywords such as ESG or CSR. Broadly-defined ESG questions further include discussions of specific E/S/G dimensions (e.g., pollution, labor practices, board diversity) without explicit mentions of ESG or CSR terminology. A comprehensive list of search terms can be found in Appendix D. Panel B summarizes question-level statistics generated by a supervised BERT-based machine learning model, following the methodology of Lee and Zhong (2022). Specifically, we manually labeled 10% of randomly sampled questions and trained the model to classify the remaining 90%. We further validated the model's output for narrowly-defined ESG questions and ESG rating questions against keyword lists from Appendix D. Large-scale survey-like questions (1,087 in total) were excluded to prevent distortion of proportions in Panel B. Subtopics add up to the count and ratio of their parent topic.

Table 2. Balance Table Across Treatment and Crosscut Arms

Statistics	C	T1	T2	T3	T4	C1A	C1B
Number of Firms	1900	744	736	736	736	1772	1180
Age	24	23 (t=-0.85, p=0.40)	24 (t=1.19, p=0.23)	24 (t=-0.09, p=0.92)	23 (t=-1.06, p=0.29)	24 (t=0.04, p=0.97)	24 (t=-0.68, p=0.50)
Employees	4747	5103 (t=0.53, p=0.59)	5177 (t=0.59, p=0.55)	5187 (t=0.59, p=0.56)	5714 (t=0.86, p=0.39)	5170 (t=0.77, p=0.44)	5482 (t=0.93, p=0.35)
Market Value	135	131 (t=-0.22, p=0.82)	141 (t=0.27, p=0.79)	129 (t=-0.30, p=0.76)	153 (t=0.82, p=0.41)	135 (t=0.02, p=0.99)	143 (t=0.39, p=0.70)
ROA	0.03	0.02 (t=-1.03, p=0.30)	0.03 (t=0.64, p=0.52)	0.02 (t=-1.23, p=0.22)	0.03 (t=0.91, p=0.37)	0.03 (t=-0.56, p=0.58)	0.03 (t=-0.01, p=0.99)
Questions Received in 2023	84	78 (t=-1.52, p=0.13)	82 (t=-0.62, p=0.54)	80 (t=-0.91, p=0.36)	78 (t=-1.55, p=0.12)	78 (t=-1.71, p=0.09)	81 (t=-0.88, p=0.38)
Follower Count in 2023	130	129 (t=-0.11, p=0.91)	142 (t=1.32, p=0.19)	133 (t=0.41, p=0.68)	137 (t=0.84, p=0.40)	135 (t=0.73, p=0.47)	136 (t=0.86, p=0.39)
Average ESG Ratings	0.47	0.46 (t=-1.55, p=0.12)	0.48 (t=0.72, p=0.47)	0.47 (t=-0.31, p=0.76)	0.46 (t=-1.75, p=0.08)	0.46 (t=-1.19, p=0.23)	0.47 (t=-0.57, p=0.57)
Historical ESG Reports	1.31	1.27 (t=-0.43, p=0.67)	1.44 (t=1.36, p=0.17)	1.47 (t=1.66, p=0.10)	1.37 (t=0.58, p=0.56)	1.38 (t=0.96, p=0.34)	1.40 (t=1.07, p=0.28)
Mentions of ESG to Institutional Investors	0.02	0.02 (t=-0.61, p=0.54)	0.02 (t=-1.00, p=0.32)	0.02 (t=-0.68, p=0.50)	0.03 (t=0.89, p=0.37)	0.03 (t=0.63, p=0.53)	0.01 (t=-1.87, p=0.06)
Regulation Violation Media Reports	0.28	0.27 (t=-0.18, p=0.85)	0.19 (t=-1.08, p=0.28)	0.18 (t=-1.37, p=0.17)	0.28 (t=-0.01, p=0.99)	0.25 (t=-0.45, p=0.66)	0.20 (t=-1.03, p=0.30)
Supply Chain Issue Media Reports	0.05	0.02 (t=-1.31, p=0.19)	0.06 (t=0.14, p=0.89)	0.05 (t=-0.18, p=0.86)	0.06 (t=0.23, p=0.82)	0.04 (t=-0.43, p=0.67)	0.06 (t=0.09, p=0.93)

Notes: This table reports balance tests comparing pre-experiment characteristics across treatment arms (T1-T4) and crosscut arms (C1A-C1B). The mean values for each variable for firms within each arm are shown outside the parentheses. Inside the parentheses, we provide the t-statistics and p-values from the t-tests comparing each treatment or crosscut arm to the control group. All comparisons are statistically insignificant ($p > 0.05$), confirming that the randomization was well executed.

Supplemental Appendix

Appendix A. Sample Messages on the Platforms

A1 Online Q&A platforms

董秘你好：我关注贵公司了好几年，但发现你们ESG评分总是不高，在万得、MSCI等机构打分都在行业中下游(CC)。想问董事会是否重视社会的 ESG 大趋势？是否有提高 ESG 重要性的计划？

[English Translation] Dear Board Secretary: I have been following your company for several years, but I have noticed that your ESG scores have consistently been low, with ratings from institutions like Wind and MSCI placing you in the lower tier of the industry (CC). I would like to ask if the board is paying attention to the growing trend of ESG in society. Are there any plans to enhance the importance of ESG?

请问公司领导怎么看待 ESG？我发现贵公司在商道融绿和 MSCI 的 ESG 评级都较低(CCC 和 CC)，而且和同行业领先水准相比还有进步空间。最近正在召开联合国气候大会，公司有没有提升 ESG 雄心的计划？

[English Translation] May I ask how the company leaders view ESG? I have noticed that your company's ESG ratings from Syntao Green Finance and MSCI are relatively low (CCC and CC), and there is room for improvement compared to the leading standards in the industry. With the recent United Nations Climate Conference taking place, does the company have any plans to increase its ESG ambitions?

A2 Stock forums and social media

近期在投资者论坛看到了和公司 ESG 表现相关的问题，大家怎么看待现在 ESG 这个趋势？ESG 有用吗？

[English Translation] Recently, I saw questions related to the firm's ESG performance at the investor forum. What does everyone think about the current trend of ESG? Is ESG useful?

有网友在互动平台问了企业 ESG 的问题，但没收到董秘回复。关于 ESG，各位怎么看？

[English Translation] Some people asked questions about the company's ESG on the interaction platform but did not receive a response from the board secretary. What do you think about ESG?

Appendix B. Details of the Experiment Implementation

Our experiment started on December 4, 2023 and concluded on April 1, 2024. We recruited a team of 20 research assistants and divided them into three groups. The first group was responsible for drafting and sending ESG inquiries on Q&A platforms. Each assistant managed two to three accounts to avoid concentrating ESG questions within a small number of accounts. Their duties included consulting the latest ESG ratings of listed firms from our database, phrasing the questions using various rhetorical skills, and sending the questions to firm management teams according to a prespecified schedule. The second group conducted quality control and message refinement. Prior to dissemination, this team reviewed all drafted messages to ensure they reflected the tone, style, and level of sophistication typical of genuine investor inquiries. They also checked the consistency in the information and sentiment of our messages across research assistants and treated firms. The third group forwarded 40% of our messages to investor forums and social media, contributing to the C1B crosscut arm. They took forwarding actions within a week after the original post on the Q&A platforms and tailored the messages depending on whether the firms had provided any replies. They also added two to three comments using different accounts to keep the posts active after two to three days.

The timeline of our experiment is illustrated in Figure A4. For the treatment arms, we raised 5,908 questions covering 2,945 firms on the Q&A platforms (see Panel A). We initially spread the questions evenly across weekdays, but the actual posting days varied due to censorship delays by platform administrators. Additionally, because we raised a lot of questions, sometimes the censorship process took a long time, so we decided to halve the posting frequency two weeks after the start of our experiment. These contingencies are unlikely to bias our causal estimates, as censorship decisions are primarily aimed at checking for question duplication and are independent of firm characteristics. For the crosscut arm C1B, we forwarded 2,359 questions linked with 1,180 firms to each of the three platforms (Guba, Xueqiu, and Weibo) (see Panel B). The time interval between the original post and the forwarded post was randomized between one to seven days, regardless of whether firms had provided a response. Although the active intervention phase lasted four months, we collected data for a whole year (July 1, 2023–June 30, 2024) to capture both pre-treatment trends and post-treatment outcome dynamics.

Appendix C. Addressing Endogeneity Concerns in Online Responses

Several distinctive features of Q&A platforms help mitigate potential endogeneity concerns in our analysis. First, while firms actively engage within platform communities, we find minimal evidence of strategic answer replication across companies. Table A2 reveals no statistically significant difference in treatment effects between early- and late-treated firms. This aligns with Figure A6 (Panel B), where the mean cross-firm answer similarity is merely 0.13. This lack of systematic imitation suggests firms prioritize original responses, alleviating concerns about cross-firm spillover effects.

Second, AI-generated responses appear unlikely, given our experimental timeline. The study period preceded the widespread adoption of Chinese large language models (LLMs), and ChatGPT, the only major LLM available, restricted access for mainland users. This point is further supported by Table A3 and Figure A6 (Panel A), which demonstrate substantial variation in responses across treatment rounds that would be improbable with automated content production.[1]

Third, user anonymity limits potential response bias. As most platform participants are anonymous retail investors, firms have neither the means nor the incentive to tailor responses based on user profiles. We find no evidence that firms identified our research team or questioned the intent of our posts. This is confirmed in Table A4, which shows minimal differences in response quality between the Shenzhen platform (where user histories are hidden) and the Shanghai platform (where they are visible).

Fourth, institutional safeguards ensure response quality. Board secretaries bear legal responsibility for the accuracy of answers under stock exchange oversight. Figure A7 demonstrates this accountability: firms' ESG ratings from third-party agencies strongly correlate with both response length (Panel A) and sentiment scores (Panel B). These patterns suggest our observed treatment effects reflect substantive efforts rather than superficial "ESG-washing." This conclusion is further reinforced by our offline behavior analysis in Section V.2.

[1] These findings also suggest the presence of response fatigue in repeated information treatment. As Table A3 demonstrates, initial RCT messages elicit responses with 75.6% greater length and 107% higher sentiment scores than later-round counterparts. While our intervention proves effective given the previously limited discussion of ESG topics on Q&A platforms, repeated interventions targeting the same firms may yield diminishing returns unless they introduce substantively new information or perspectives.

Appendix D. ESG Keyword Taxonomy

This appendix presents our keyword taxonomy for analyzing ESG discussions, assessing response quality, identifying spillovers, and quantifying ESG mentions in investor communications. Developed through a manual review of ESG rating methodologies and corporate ESG reports, the dictionary employs two classification tiers: a narrow set of explicit ESG/CSR terms and a broader collection of E, S, and G-related keywords. Originally compiled in Chinese to align with the linguistic context, we provide parallel English translations for reference. All keyword lists are formatted with semicolon delimiters to ensure consistency and clarity.

Narrow Definition (Original): ESG; CSR; 环境、社会、治理; 环境、社会和治理; 环境、社会与治理; 环境、社会及治理; 社会责任

Narrow Definition (English Translation): ESG; CSR; Environment, Society, Governance; Environment, Society and Governance; Environment, Society & Governance; Environment, Society and Corporate Governance; Social Responsibility

E Keywords (Original): 环境保护; 保护环境; 环保; 可持续; SDG; 绿色发展; 绿色技术; 绿色转型; 气候变化; 全球变暖; 净零; 碳中和; 碳达峰; 双碳; 低碳; 碳市场; 气候风险; 气候适应; 减排; 碳足迹; 碳管理; 范围 1; 范围 2; 范围 3; 范围一; 范围二; 范围三; 脱碳; 京都议定书; 碳强度; 雾霾; 污染; 排放; 废气; 烟尘; 化石燃料; 温室气体; 二氧化碳; 二氧化硫; 一氧化碳; 氮氧化物; 硫氧化物; 颗粒物; GHG; CO2; SO2; CO; NOx; NOX; SOx; SOX; PM2.5; 排污; 污水; 废水; 环境风险; 环境监测; 放射性; 有害物质; 循环利用; 循环经济; 废弃物; 回收; 废物管理; 固体废物; 固废; 危废; 化学物质; 水资源; 可再生; 新能源; 节能; 能源效率; 能源消耗; 能耗; 电力消耗; 资源利用效率; 资源利用率; 再利用; 生态保护; 生态补偿; 绿色生态; 生物多样性; 自然资源; 生态环境; 野生动物; 造林; 生态修复; CCER; 碳汇

E Keywords (English Translation): Environmental protection; Environmental preservation; Environmental conservation; Sustainability; SDG (Sustainable Development Goals); Green development; Green technology; Green transition; Climate change; Global warming; Net zero; Carbon neutrality; Carbon peak; Dual-carbon strategy; Low-carbon; Carbon market; Climate risk; Climate adaptation; Emissions reduction; Carbon footprint; Carbon management; Scope 1; Scope 2; Scope 3; Scope I; Scope II; Scope III; Decarbonization; Kyoto Protocol; Carbon intensity; Smog; Pollution; Emissions; Exhaust gas; Smoke and dust; Fossil fuels; Greenhouse gases; Carbon dioxide; Sulfur dioxide; Carbon monoxide; Nitrogen oxides; Sulfur oxides; Particulate matter; GHG; CO2; SO2; CO; NOx; NOX; SOx; SOX; PM2.5; Effluent discharge; Wastewater; Industrial effluent; Environmental risk; Environmental monitoring; Radioactivity; Hazardous substances; Recycling; Circular economy; Waste; Reclamation; Waste management; Solid waste; Solid refuse; Hazardous waste; Chemical substances; Water resources; Renewable energy; New energy; Energy conservation; Energy efficiency; Energy consumption; Energy use; Electricity consumption; Resource efficiency; Resource utilization rate; Reuse; Ecological conservation; Ecological compensation; Green ecology; Biodiversity; Natural resources; Ecological environment; Wildlife; Afforestation; Ecological restoration; CCER (China Certified Emission Reduction); Carbon sink

S Keywords (Original): 人权; 劳工权益; 劳工关系; 童工; 劳动合同; 最低工资; 工作环境; 健康与安全; 员工安全; 安全生产; 安全培训; 受伤率; 歧视; 骚扰; 不当行为; 保密性; 数据保护; 客户隐私; 消费者隐私; 隐私保护; 数据安全; 权益保护; 保护性措施; 合规性; 违规行为; 民主; 社会公正; 社会影响; 社会贡献; 社会责任; 社会投资; 社会资本; 公益; 福祉; 社区关系; 当地社区; 社区参与; 社区发展; 社区贡献; 社区福利; 社区影响; 当地就业; 迁移安置; 文化遗产; 原住民; 供应链管理; 供应链可持续性; 产品质量; 产品安全; 质量管控; 负责任营销; 食品安全; 客户体验; 客户满意度; 客户福利; 公共关系; 利益相关方参与; 多元化政策; 多元与包容; 性别平等; 社会保障; 员工福利; 员工流动率; 员工敬业度; 职业发展; 绩效管理; 公平薪酬; 同工同酬; 工伤; 员工培训; 员工满意度

S Keywords (English Translation): Human rights; Labor rights; Labor relations; Child labor; Labor contracts; Minimum wage; Working conditions; Health and safety; Employee safety; Workplace safety; Safety training; Injury rate; Discrimination; Harassment; Misconduct; Confidentiality; Data protection; Customer privacy; Consumer privacy; Privacy protection; Data security; Rights protection; Protective measures; Compliance; Violations; Democracy; Social equity; Social impact; Social contribution; Social responsibility; Social investment; Social capital; Public welfare; Well-being; Community relations; Local community; Community engagement; Community development; Community contribution; Community welfare; Community impact; Local employment; Resettlement; Cultural heritage; Indigenous peoples; Supply chain management; Supply chain sustainability; Product quality; Product safety; Quality control; Responsible marketing; Food safety; Customer experience; Customer satisfaction; Customer welfare; Public relations; Stakeholder engagement; Diversity policy; Diversity and inclusion; Gender equality; Social security; Employee benefits; Employee turnover; Employee engagement; Career development; Performance management; Fair compensation; Equal pay for equal work; Work-related injuries; Employee training; Employee satisfaction

G Keywords (Original): 公司治理; 企业治理; 治理结构; 治理框架; 治理机制; 治理政策; 治理标准; 治理改进; 治理评估; 治理监督; 治理风险; 治理合规; 治理报告; 治理文化; 治理责任; 公司责任; 企业道德; 职业道德; 道德规范; 道德标准; 行为准则; 公司文化; 公司结构; 董事会结构; 董事会多样性; 性别多样性; 董事会独立性; 独立董事; 审计委员会; 薪酬委员会; 股东利益; 股东权益; 股东权利; 股东投票; 股东提案; 股东沟通; CEO 薪酬; 高管薪酬; 透明度; 信息披露; 数据真实性; 数据的真实性; 合规管理; 合规性; 风险管理; 风险管控; 突发事件响应; 内部控制; 内部审计; 外部审计; 独立审计; 审计独立性; 反腐; 腐败; 贪腐; 贿赂; 造假; 漏税; 避税; 偷税; 逃税; 诉讼; 官司; 恶性竞争; 第三方尽职调查; 黑名单筛查; 危机管理; 利益冲突

G Keywords (English Translation): Corporate governance; Enterprise governance; Governance structure; Governance framework; Governance mechanism; Governance policy; Governance standards; Governance improvement; Governance assessment; Governance oversight; Governance risk; Governance compliance; Governance reporting; Governance culture; Governance responsibility; Corporate responsibility; Business ethics; Professional ethics; Code of ethics; Ethical standards; Code of conduct; Corporate culture; Corporate structure; Board structure; Board diversity; Gender diversity; Board independence; Independent directors; Audit committee; Compensation committee; Shareholder interests; Shareholder rights; Shareholder privileges; Shareholder voting; Shareholder proposals; Shareholder communication; CEO compensation; Executive compensation; Transparency; Information disclosure; Data authenticity; Data veracity; Compliance management; Compliance; Risk management; Risk control; Emergency response; Internal controls; Internal audit; External audit; Independent audit; Audit independence; Anti-corruption; Corruption; Graft; Bribery; Fraud; Tax leakage; Tax avoidance; Tax fraud; Tax evasion; Litigation; Legal disputes; Unfair competition; Third-party due diligence; Blacklist screening; Crisis management; Conflict of interest

Appendix E. Classification of Investors' Questions and Firms' Answers in Communication Transcripts

This appendix outlines our methodology for distinguishing investors' questions from firms' answers in a dataset of 22,896 communication transcripts. Our objective is to isolate whether the elevated ESG discourse identified in Panel B of Figure 6 originates from firms' voluntary disclosures or investor-driven inquiries. Given the impracticality of manual classification at this scale, we implement a hybrid human-machine protocol to ensure accuracy while minimizing subjectivity.

The classification process begins with keyword-based labeling. We flag paragraphs containing explicit question identifiers such as "问题" (question), "请问" (may I ask), "?", "Q," or "q" as investor questions. Responses are identified via keywords like "回复" (reply), "答" (answer), "A," or contextual markers indicating corporate replies. To minimize false positives, we intentionally restrict this keyword list to 12 high-precision terms and manually validate a 10% random sample.

For transcripts lacking explicit identifiers, we deploy ChatGPT 4.0 with the following structured prompt:

[Original Chinese Prompt] "根据以下文本内容，分别总结出提问交流环节中的问题与公司的回复（提取原文进行回答），问题与回复这两个回答之间一定要用#号隔开，不同问题以及不同回答之间用^号隔开。（格式为：问题：1.XXX^2.XXX... # 回复：1.XXX^2.XXX... 举例说明，如果文本为：1. 对于养老行业,公司是否有相关产品或是产业布局?\r\n\r\n答:公司以多模态生物识别技术及计算机视觉技术为核心,坚持自主技术创新,并持续关注相关技术创新与公司产品和服务结合的可能性。公司近期在生态业务布局了智能护理产品,该部分业务暂未形成销售,具有一定的不确定性。\r\n\r\n2. 公司近几年营收情况较为平稳,主要是什么原因呢?\r\n\r\n答:近两年国内市场需求有所减弱,公司基于整体战略布局考量,对低毛利甚至负毛利的业务板块进行了优化调整,国内业务收入有所下滑,但公司的海外业务收入保持平稳增长。则回答应该为：问题：1.对于 养老行业,公司是否有相关产品或是产业布局?^2.公司 近几年营收情况较为平稳,主要是什么原因呢? # 回复：1.公司以多模态生物识别技术及计算机视觉技术为核心,坚持自主技术创新,并持续关注相关技术创新与公司产品和服务结合的可能性。公司近期在生态业务布局了智能护理产品,该部分业务暂未形成销售,具有一定的不确定性。^2. 近两年国内市场需求有所减弱,公司基于整体战略布局考量,对低毛利甚至负毛利的业务板块进行

了优化调整,国内业务收入有所下滑,但公司的海外业务收入保持平稳增长。）以下为文本：”

[English Translation] “From the following text, summarize the following information: investor questions and the company’s replies during the Q&A session (provide verbatim extracts). Separate questions and replies with a # symbol, and separate different questions and replies with a ^ symbol. Format as: Questions: 1.XXX^2.XXX... # Replies: 1.XXX^2.XXX... For example, if the text is: 1. For the elderly care industry, does the company have relevant products or strategic plans?\r\n\r\n Answer: The company focuses on multimodal biometrics and computer vision technologies, prioritizing independent innovation. We are exploring opportunities to integrate these technologies with our products and services. Recently, we developed smart nursing products under our ecosystem business, though sales have not yet commenced, and uncertainties remain.\r\n\r\n2. Why has the company’s revenue remained stable in recent years?\r\n\r\n Answer: Domestic demand has weakened over the past two years. As part of our strategic optimization, we adjusted low-margin business segments, leading to reduced domestic revenue. However, overseas revenue has grown steadily. The output should be formatted as: Questions: 1. For the elderly care industry, does the company have relevant products or strategic plans?^2. Why has the company’s revenue remained stable in recent years? # Replies: 1. The company focuses on multimodal biometrics and computer vision technologies, prioritizing independent innovation. We are exploring opportunities to integrate these technologies with our products and services. Recently, we developed smart nursing products under our ecosystem business, though sales have not yet commenced, and uncertainties remain.^2. Domestic demand has weakened over the past two years. As part of our strategic optimization, we adjusted low-margin business segments, leading to reduced domestic revenue. However, overseas revenue has grown steadily. The following is the text:”

We employ unconventional delimiters (# and ^) to prevent overlap with natural language text. The model receives a templated example to ensure standardized output formatting into two columns: Investors’ Questions and Firms’ Answers. Using the ESG keyword taxonomy defined in Appendix C, we compute term frequencies separately for each column and perform regression analyses, generating the results shown in Table A8.

Appendix F. Trends in Alternative Market Response Measures

This appendix assesses the robustness of our main findings on market valuation using three alternative measures. First, to capture the overall firm value response, we examine market capitalization directly. Second, we analyze cumulative log returns as a straightforward, model-free measure of long-run performance. These two measures serve as direct counterparts to our six-month analysis in the main text. Third, responding to conventions in the finance literature, we estimate short-window cumulative abnormal returns (CAR). Standard asset pricing models used to calculate CAR, such as the Fama-French models, are best suited for short event windows, as the assumption of stable factor loadings (betas) becomes less tenable over longer horizons (Kothari & Warner, 2007; MacKinlay, 1997). Our main six-month analysis window is thus ill-suited for a CAR-based methodology. Instead, we use CAR to test for immediate market reactions within one month of our intervention, complementing our primary long-run analysis.

E1 Long-Run Model-Free Benchmarks: Market Value and Cumulative Returns

We first present model-free evidence using two alternative long-run valuation metrics: the daily market capitalization of tradable A-shares and the cumulative log return. Figure A12 plots the evolution of these measures over the six-month post-treatment period, paralleling the market capitalization analysis in Figure 7 and Figure 10.

The results provide strong corroboration for our main findings. Panels A and C of Figure A12 show a negligible average treatment effect on both market value and cumulative returns, consistent with Figure 7. Panels B and D, which disaggregate the effects by treatment arm, mirror the heterogeneous patterns reported in Figure 10. Inquiries about environmental issues lead to a statistically and economically significant increase in both market value and cumulative returns. In contrast, inquiries about governance issues trigger a persistent negative trend in these valuation metrics. The effect of social inquiries is statistically indistinguishable from zero. These patterns confirm that our main results are robust and not an artifact of using closing prices as the primary outcome variable.

E2 Short-Run Analysis using Cumulative Abnormal Returns (CAR)

To examine the market's immediate reaction to our information treatment, we conduct a short-run event study using CAR following the finance literature. We estimate abnormal returns using two benchmark models: the Fama-French three-factor model and the five-factor model.

Methodology. The procedure involves two steps. First, for each firm i, we estimate the parameters of the asset pricing models using daily return data from a pre-event estimation window of [-160, -41] trading days, where day 0 is the date of the intervention. In line with standard event study practices (Acemoglu et al., 2016; MacKinlay, 1997), we exclude the [-40, -1] period to mitigate potential contamination from pre-event information leakage, even though such anticipation is unlikely in our randomized experimental design. The models are specified as:

Fama-French Three-Factor Model:

$$R_{i,t} - RF_t = \alpha_i + \beta_{i,MKT} MKT_t + \beta_{i,SMB} SMB_t + \beta_{i,HML} HML_t + \epsilon_{i,t} \tag{1}$$

Fama-French Five-Factor Model:

$$R_{i,t} - RF_t = \alpha_i + \beta_{i,MKT} MKT_t + \beta_{i,SMB} SMB_t + \beta_{i,HML} HML_t + \beta_{i,RMW} RMW_t + \beta_{i,CMA} CMA_t + \epsilon_{i,t} \tag{2}$$

where $R_{i,t} - RF_t$ is excess return for asset i at time t (above the risk-free interest rate). MKT_t, SMB_t, HML_t, RMW_t, and CMA_t are the standard market, size, value, profitability, and investment factors, respectively. The coefficients of interest are a set of β_i's, which represent the marginal contribution of market factors to each firm's expected returns. The estimated intercept, α_i, is insignificant for the vast majority of firms in our sample, suggesting the models effectively capture expected returns during the estimation period.

In the second step, we predict the expected return, $E[R_{i,t}]$, for each firm i during the post-event window using the estimated firm-specific parameters $(\hat{\alpha}_i, \hat{\beta}_i)$ and the realized factor returns on day t. The abnormal return (AR) is the difference between the actual and expected return:

$$AR_{i,t} = R_{i,t} - E\left[R_{i,t}\right] \tag{3}$$

The cumulative abnormal return (CAR) for the window $[t_1, t_2]$ is the sum of daily abnormal returns:

$$CAR_i(t_1, t_2) = \sum_{t=t_1}^{t_2} AR_{i,t} \tag{4}$$

Results. We calculate CAR over three short-term event windows: [0,4] (one week), [0,9] (two weeks), and [0,20] (one month). We then regress the firm-specific CARs on our treatment indicators. The results are summarized in Table A13.

Across all models and event windows, the estimated treatment effects on CAR are not statistically significant. This is expected, as any immediate market reaction would likely be small, preceding the tangible offline ESG actions (e.g., ESG report publication, ESG rating updates) that drive the larger, long-term valuation shifts.

However, the signs and relative magnitudes of the coefficients are remarkably consistent with our six-month findings. Across all specifications, E inquiries generate a positive (though statistically insignificant) CAR, while G inquiries consistently produce a negative CAR. The point estimates for S inquiries are close to zero, situated between those for E and G. This short-run pattern aligns with the initial market response documented by our dynamic difference-in-differences estimates in Figure 10.

In sum, the short-window analysis suggests that the market's initial reaction is directionally consistent with the long-term equilibrium effects. The full valuation impact appears to materialize over subsequent months as firms undertake and disclose costly ESG actions, and this new information is gradually impounded into stock prices. These corroborating results reinforce our interpretation that the market response is driven by the signaling content of firms' substantive, offline ESG actions rather than by the initial online engagement alone.

Appendix G. ESG as a Signaling Device: An Illustrative Model

To explore the motivations behind firms' ESG actions and guide the subsequent analysis, we develop an illustrative model building on the seminal signaling framework by Spence (1973). Our central argument posits that firms undertake costly ESG actions to signal their quality under information asymmetry. We derive key propositions from this illustrative model, which will guide our heterogeneity analysis in Section VII.

The market consists of two sets of risk-neutral players: firms and investors. A firm's productivity (quality/type) θ is drawn from a continuous distribution $\Theta = [\underline{\theta}, \overline{\theta}]$ with a density function $f(\theta) > 0$ at all points. θ is publicly observable with a probability φ, where φ is public information and unalterable by firms. Productivity θ and transparency φ are orthogonal attributes for each firm.

Investors, who are the owners of the firms, collectively determine market value based on available information. Their beliefs follow the Bayesian rule. Among these investors, a fraction γ are ESG-conscious, incorporating firms' ESG performance in their valuation process. The remaining investors do not consider ESG to be relevant to firms' market value. The investors operate in a competitive market, where each expects to earn zero profit in equilibrium.

Firms may use ESG as costly signals e to convey their inherent type θ to uninformed investors. These ESG efforts are generally not directly linked to a firm's core business operations, allowing firms to enhance their social reputation without disclosing trade secrets. For simplicity, we assume that ESG efforts do not directly enhance firm productivity but serve solely as signals of their type. The results remain robust even when we relax this assumption.

Following Spence (1973), we make the following assumptions about the signaling cost $c(e, \theta)$:

1) $c(0, \theta) = 0$: No signaling effort implies no signaling cost.
2) $c_e(e, \theta) > 0$: Higher signaling effort results in higher signaling cost.
3) $c_{ee}(e, \theta) > 0$: The cost function is convex with respect to signaling effort.
4) $c_\theta(e, \theta) < 0$: Higher firm productivity leads to lower signaling cost.
5) $c_{e\theta}(e, \theta) < 0$: Higher firm productivity reduces the marginal signaling cost with respect to signaling effort.

The first four assumptions are standard and straightforward to justify. The last assumption suggests that the marginal cost of increasing ESG signaling effort decreases with higher firm productivity/quality. This can be supported by the fact that higher-quality firms generally have more capable personnel and resources, which enables them to achieve ESG signaling at lower additional expenditure. Without loss of generality, we assume $c(e, \theta) = c(\frac{e}{\theta})^2$ ($c > 0$) to obtain a closed-form solution.

The timeline of actions is as follows. In the first period, firms choose their ESG signaling levels e based on their own type θ and transparency φ. In the following period, there is a probability φ that θ becomes public knowledge, allowing investors to price firms based on their true type θ. Alternatively, with probability $(1 - \varphi)$, θ remains private information, and uninformed rational investors infer firms' inherent quality based on the observed ESG signals e. In the concluding period, θ is fully revealed, and firms and investors achieve their respective profits. We assume no discount between periods.

Given this setup, we can formulate the following optimal strategies for each player.

Firms' optimal strategy:

$$e(\theta, \varphi, \gamma) \in arg\max_{e} \varphi\theta + (1 - \varphi)[\gamma w_1(e, \varphi) + (1 - \gamma)w_2(\varphi)] - c(e, \theta) \quad (5)$$

where $w_1(e, \varphi)$ and $w_2(\varphi)$ represent the market valuation outcomes for ESG-conscious and non-ESG-conscious investors, respectively. These outcomes are weighted by their market share, which can vary among firms based on the composition of their investors.

ESG-conscious investors' optimal strategy:

$$w_1(e, \varphi) \in arg\ \max_{w_1} \int_{\underline{\theta}}^{\overline{\theta}} \mu_i(e, \varphi)\theta_i d\theta_i - w_1(e, \mu) \quad (6)$$

where $\mu_i(e, \varphi)$ is investors' belief that a firm is of type θ_i given the observed signal and transparency level. This belief obeys the Bayesian rule.

Non-ESG-conscious investors' optimal strategy:

$$w_2(\varphi) = \varphi\theta + (1 - \varphi)\mathbb{E}[\theta] \quad (7)$$

which is not a function of ESG signaling effort e because this group of investors does not consider ESG to be value-relevant. They base their valuation decisions solely on the availability of accurate productivity information.

The optimization problems may lead to multiple types of equilibria. For real-world relevance, we only focus on separating perfect Bayesian equilibria (PBE), where $e^*(\theta, \varphi) \neq e^*(\theta', \varphi')\ \forall(\theta, \varphi) \neq (\theta', \varphi')$. In other words, we limit our attention to cases where different firms supply different levels of ESG signals to explore the drivers of their heterogeneity. The first-order condition of firms' profit maximization is the following:

$$(1 - \varphi)\gamma w_{1e}(e, \varphi) - \frac{2ce}{\theta^2} = 0 \tag{8}$$

Note that the optimal signal under perfect transparency $\overline{\varphi} = 1$ is always zero. This is because when $\overline{\varphi} = 1$, the partial derivative of firms' profit with respect to e is $-\frac{2ce}{\theta^2} \leq 0$, and the firms' optimal strategy is to minimize their signaling efforts, i.e., $e^* = 0$.

For firms with $\theta \in [\underline{\theta}, \overline{\theta}]$ and $0 \leq \varphi < 1$, we utilize the zero-profit condition for investors ($w_1(e, \varphi) = \theta$) and Equation (14) can be rewritten as:

$$w_1(e, \varphi)^2 w_{1e}(e, \varphi) = \frac{2ce}{(1-\varphi)\gamma} \tag{9}$$

Corollary. $w_{1e}(e, \varphi) \geq 0$: Investors' valuation of firms is positively correlated with firms' ESG signals.

Solving this simple differential equation, we obtain:

$$w_1(e, \varphi) = \left[\frac{3ce^2}{(1-\varphi)\gamma} + C\right]^{\frac{1}{3}}, where\ C\ is\ a\ constant \tag{10}$$

From Equation (16), the separating PBE signaling path can be summarized as:

$$e^*(\theta, \varphi, \gamma) = \sqrt{\frac{(1-\varphi)\gamma[\theta^3 - C]}{3c}} \tag{11}$$

Propositions. In separating PBEs, firms' optimal ESG signaling $e^*(\theta, \varphi, \gamma)$ satisfies:

1) $\frac{\partial e^*}{\partial \theta} > 0$: Firms with higher productivity send more ESG signals.

2) $\frac{\partial e^*}{\partial \varphi} < 0$: Firms with lower transparency send more ESG signals.

3) $\frac{\partial e^*}{\partial \gamma} > 0$: Firms with more ESG-conscious investor bases send more ESG signals.

Appendix H. Construction of Firm Productivity Measures

We employ four variables, return on assets (ROA), return on equity (ROE), and two total factor productivity (TFP) measures, to proxy firms' unobserved productivity levels. ROA is defined as net income divided by total assets, reflecting a firm's efficiency in generating profits from its asset base. ROE, calculated as net income relative to shareholders' equity, measures the profitability relative to equity investment. Both ratios capture financial performance and resource utilization efficiency, with higher values indicating superior managerial effectiveness. These data are obtained from the CSMAR database prior to the start of our experiment.

In addition to ROA and ROE, we manually compute two TFP measures using value-added and revenue-based approaches and input data from CSMAR. Our methodology adapts the control function approach proposed by Ackerberg et al. (2015) (ACF) to address endogeneity in production function estimation, which builds on the Levinsohn and Petrin (2003) (LP) estimator. We estimate a Cobb-Douglas production function in logarithmic form, assuming constant returns to scale:

$$y_{it} = \beta_l l_{it} + \beta_k k_{it} + \beta_m m_{it} + \omega_{it} + \epsilon_{it} \tag{12}$$

where y_{it} denotes the logarithm of firm output, measured either as industrial value-added or revenue. l_{it}, k_{it}, and m_{it} represent logarithms of labor (employment), capital (fixed assets), and intermediate inputs, respectively. The term ω_{it} captures unobserved firm-specific productivity, assumed to follow a first-order Markov process:

$$\omega_{it} = E\left(\omega_{it} \middle| \omega_{i,t-1}\right) + u_{it} = g\left(\omega_{i,t-1}\right) + u_{it} \tag{13}$$

where u_{it} is an idiosyncratic productivity shock. The error term ϵ_{it} reflects transitory output shocks, assumed orthogonal to inputs and productivity.

A key concern in production function estimation is simultaneity bias, arising from the correlation between firms' productivity shocks and input choices. The LP-ACF approach addresses this by using intermediate inputs m_{it} as a proxy for ω_{it}, under the monotonicity condition $\omega_{it} = h_t(m_{it}, l_{it}, k_{it})$. This allows rewriting the production function as follows:

$$y_{it} = \phi_t(m_{it}, l_{it}, k_{it}) + \epsilon_{it} \tag{14}$$

Estimation proceeds in two stages. First, we obtain the predicted output $\hat{\phi}_{it}$ via nonparametric regression. Second, we recover the production function coefficients $(\beta_l, \beta_k, \beta_m)$ using moment conditions derived from the Markovian structure of productivity:

$$E(u_{it}(\beta_l, \beta_k, \beta_m)k_{it}) = 0 \tag{15}$$

$$E\big(u_{it}(\beta_l, \beta_k, \beta_m)l_{i,t-1}\big) = 0 \tag{16}$$

$$E\big(u_{it}(\beta_l, \beta_k, \beta_m)m_{i,t-1}\big) = 0 \tag{17}$$

where $u_{it}(\beta_l, \beta_k, \beta_m) = \omega_{it} - E\big(\omega_{it}\big|\omega_{i,t-1}\big)$. These conditions exploit lagged flexible inputs (labor, materials) and current capital, which is subject to adjustment costs. The estimated TFP in logs is then:

$$\widehat{\omega}_{it} = \hat{\phi}_{it} - \hat{\alpha} - \hat{\beta}_l l_{it} - \hat{\beta}_k k_{it} - \hat{\beta}_m m_{it} \tag{18}$$

and TFP in levels is $exp(\widehat{\omega}_{it})$.

For implementation, we measure value-added as the sum of fixed-asset depreciation, labor compensation, production taxes, and operating surplus, equivalent to gross output minus intermediate inputs plus value-added tax. Intermediate inputs are computed as the sum of operating costs, sales, management, and financial expenses, net of depreciation, and labor costs. We estimate the model via the "prodest" command in Stata. The resulting residuals are exponentiated to obtain TFP estimates.

Appendix I. Details of Firm Transparency Indicators

We develop a composite index of corporate transparency by synthesizing measures from prior literature across economics, finance, management, and accounting. Reflecting distinct conceptual frameworks in these fields, transparency indicators are broadly categorized into three dimensions: internal management, external relationship, and market research. For each category, we standardize and aggregate constituent indicators into sub-indices, which are then combined into a summary index. Below, we detail the theoretical rationale and definition of each component.

Internal Management Transparency Index: The internal management transparency index reflects the accessibility and clarity of information related to a firm's governance and operational decisions. Drawing on established metrics from the literature, the index incorporates four components. First, **state ownership** is a binary indicator for state-controlled firms, which prior studies associate with reduced disclosure due to political objectives overriding market incentives (Guedhami et al., 2009). Second, **product diversification**, measured as the count of distinct product lines, proxies operational complexity. Greater diversification obscures the assessment of firm quality (Hund et al., 2010). Third, **research intensity**, defined as research expenditures scaled by market value, captures technological specialization and informational opacity, as innovation-driven firms often face higher proprietary costs of disclosure (Kankanhalli et al., 2024). Fourth, **independent board members**, calculated as the proportion of independent directors on the board, are generally linked to stronger monitoring and reduced information hoarding (Armstrong et al., 2014).

External Relationship Transparency Index: This index reflects the visibility of a firm's interactions with suppliers, customers, and global markets. We include four indicators derived from the CSMAR database. **Supply chain concentration**, calculated as the average percentage of a firm's purchases from its top five suppliers and sales to its top five customers, is inversely related to transparency. Dispersed supply chains hinder monitoring and reduce operational visibility (Kim & Davis, 2016). Similarly, **customer concentration** and **supplier concentration**, measured using the Herfindahl-Hirschman Index (HHI) of the top five clients and suppliers, respectively, reflect information asymmetry along the supply chain.[2] Lower concentration disperses performance signals, raising monitoring costs (Gualandris et al., 2021). Finally, **share of overseas revenues**, computed as foreign sales relative to market value, introduces cross-border informational frictions, impeding domestic investors' ability to verify performance (Hitt et al., 1997).

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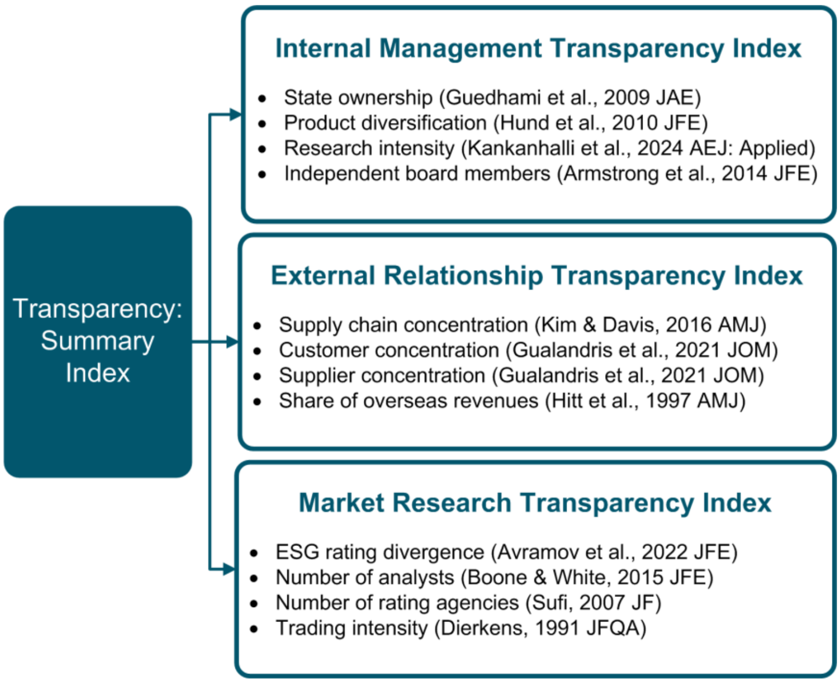
[2] Formulas: Customer HHI $= \sum_{i=1}^{5} \left(\frac{\text{Sales to Customer } i}{\text{Total Sales}}\right)^2$, Supplier HHI $= \sum_{i=1}^{5} \left(\frac{\text{Purchases from Supplier } i}{\text{Total Purchases}}\right)^2$

Market Research Transparency Index: The market research index assesses the availability and consensus of third-party evaluations of firm quality. It comprises four components. **ESG rating divergence**, calculated as the cross-agency standard deviation of ESG percentile rankings, signals disagreement among evaluators. Higher divergence implies ambiguous or withheld information (Avramov et al., 2022; Ertan et al., 2025). **Number of analysts** and **number of rating agencies**, each scaled by firm market value, directly proxy transparency, as greater analyst coverage and more extensive credit ratings correlate with richer public information (Boone & White, 2015; Sufi, 2007). Additionally, **trading intensity**, measured as the number of shares traded each day, reflects the degree of liquidity and insider information. Higher trading intensity is often associated with greater transparency, although the relationship can reverse when elevated trading activity is driven by informed traders (Dierkens, 1991).

Index Construction: For each indicator, we compute z-scores to ensure comparability across metrics. We then aggregate these standardized values into three category-level indices (internal governance, external relationships, and market information) by taking the arithmetic mean of their respective component z-scores. The overall transparency index is calculated as the equal-weighted average of these three category indices. A graphical illustration of the index structure is provided in the figure below.



Appendix J. Identification of Executives' Government Experiences

This appendix outlines our methodology for identifying political connections among corporate leaders in China. We begin with the complete résumés of chairpersons, vice-chairpersons, CEOs, and vice-CEOs from the CSMAR Director Database. To balance computational efficiency with accuracy, we implement a two-stage natural language processing protocol:

Stage 1: Experience Extraction

We instruct ChatGPT 4.0 to parse each individual's employment history, generating a structured record of current and past positions. The extraction prompt specifies:

[Original Chinese Prompt] "从以下文字中总结以下信息:姓名,目前任职单位以及职务,曾经任职的单位以及职务（回答用#号隔开,任职单位和职务用,号隔开,如有多个曾经任职单位, 曾经任职单位之间用#号隔开,如 姓名:XXX#现任职单位:XXX,现任职单位职务:XXX#曾经任职单位 1:XXX,曾经任职单位职务:XXX#曾经任职单位 2:XXX,曾经任职单位职务:XXX...未提及的写 无）:"

[English Translation] "Extract the following information from the text: Full name; current employer and position; previous employers and positions (format responses with # separators between categories, commas between employer and position, # separators between multiple previous employers. Example: Name: XXX#Current Employer: XXX, Current Position: XXX#Previous Employer 1: XXX, Previous Position 1: XXX#Previous Employer 2: XXX, Previous Position 2: XXX... If no information exists, mark as 'None')."

Stage 2: Government Affiliation Classification

We then task ChatGPT 4.0 with identifying government-related experience, including administrative levels and positions:

[Original Chinese Prompt] "从以下文本中总结信息:姓名,曾经任职的单位是否包括政府部门,所任政府部门的名称,政府部门的级别(省级,市级,区级等),在政府部门担任职务（回答用#号隔开,任职政府单位名称,任职单位级别和职务用,号隔开,如有多个曾经任职单位,曾经任职单位之间用#号隔开,如 姓名:XXX#是否曾在政府单位任职:是,曾任职政府单位名称 1:XXX,任职政府单位级别 1:XXX,曾任职职务 1:XXX#曾任职政府单位名称 2:XXX,任职政府单位级别 2:XXX,曾任职职务 2:XXX...未提及的写 无,曾经没有在政府单位任职过的写 否）:"

[English Translation] "Classify the following from the text: Full name; whether previous employers include government agencies; government agency names; administrative levels (provincial, municipal, district, etc.); government positions held (format responses with # separators between categories, commas between agency name, administrative level, and position. Example: Name: XXX#Government Employment: Yes#Government Agency 1: XXX, Administrative Level 1: XXX, Position 1: XXX#Government Agency 2: XXX, Administrative Level 2: XXX, Position 2: XXX... If no government employment exists, mark as 'No')."

Validation and Metric Construction

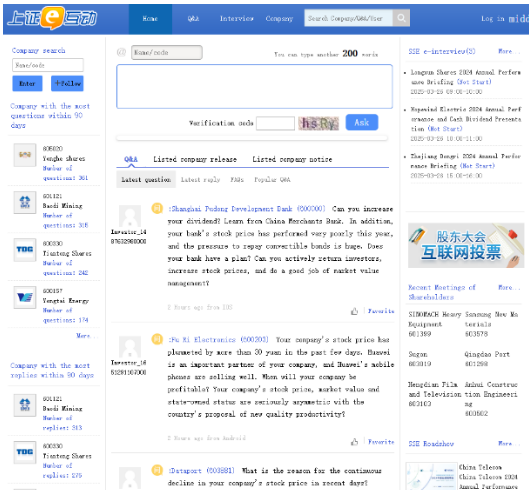
Following automated extraction, we manually audit a 10% random sample to verify accuracy. We then define our primary measure of firm-level government connections as the proportion of C-suite executives with current or former government employment. Robustness checks using alternative specifications—including binary indicators for any government-linked executives and the highest administrative level attained—yield qualitatively similar results, suggesting limited heterogeneity in political connection effects across listed firms.

Appendix K. Additional Tables and Figures

Panel A: Shenzhen Platform

(Original) (English Translation)

Panel B: Shanghai Platform



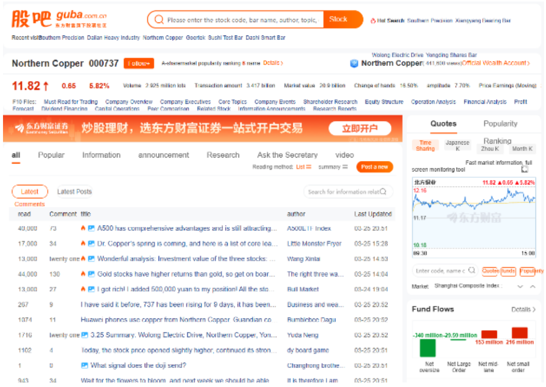
(Original) (English Translation)

Figure A1. Screenshots of Online Q&A Platforms in China (taken in March 2025)

Notes: This figure shows screenshots of the homepages of two online Q&A platforms established by the Shenzhen and Shanghai Stock Exchanges. Apart from platform statistics and announcements on the sides, the main part of the window presents the latest Q&A interactions between investors and firms. The interactions are sorted by the last update time, either by investors posting the question or firms providing an answer. All interactions are public to all users. For each question, the platform shows the target firm, its list code, the questioner ID, the interaction contents, the update time, and the number of likes. Investors are not allowed to follow up on a question other than raising a new question to the same firm.

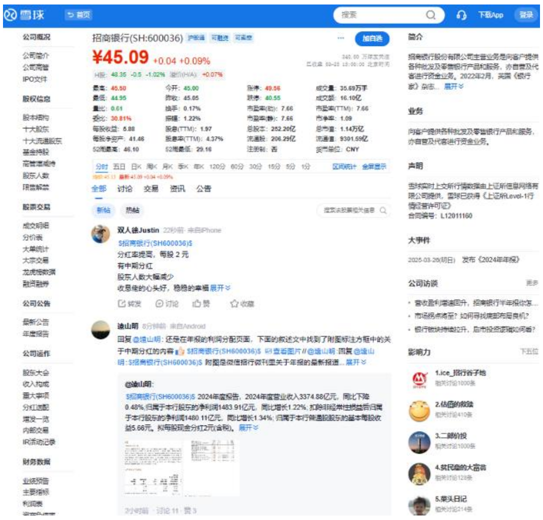
Panel A: Guba (Guba.EastMoney.com)

(Original)

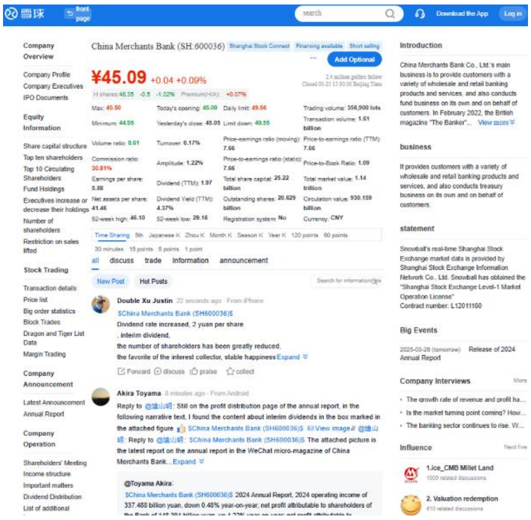


(English Translation)

Panel B: Xueqiu (xueqiu.com)



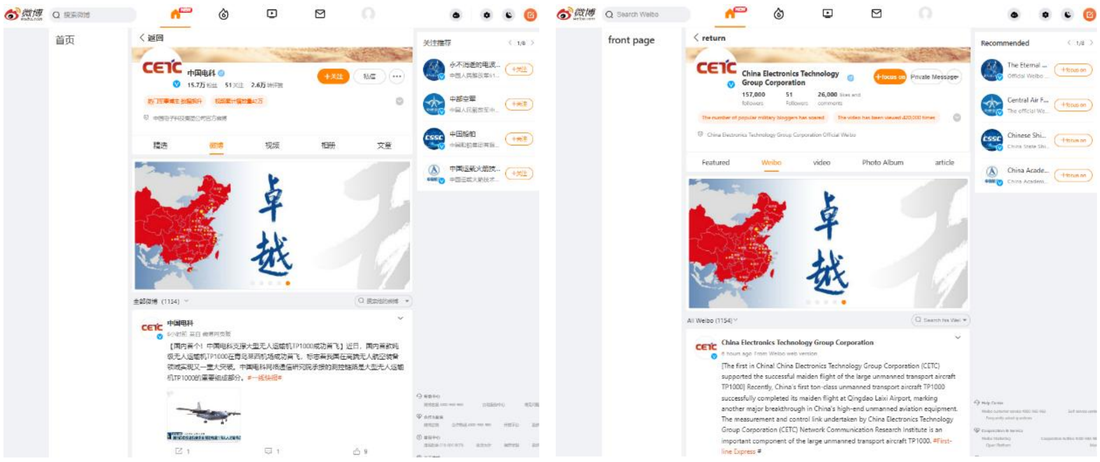
(Original)



(English Translation)

Figure A2. Screenshots of Stock Forums in China (taken in March 2025)

Notes: This figure presents screenshots of two company pages on the stock forums used in the experiment. They are arranged in a similar manner. At the top, the name and code of a listed firm are displayed, followed by recent stock return trends. The bulk of the window is dedicated to interactions between investors concerning this specific firm. For each message, the platform shows its content, original author, page views, all follow-up comments, and the latest update time. Messages can be sorted either by popularity or update time.



(Original) (English Translation)

Figure A3. Screenshot of a Listed Firm's Weibo Account (taken in March 2025)

Notes: This figure is a screenshot of a listed firm's Weibo page. At the top, it displays the name, description, and number of followers of this corporate account. The blue checkmark indicates official verification by Weibo. In the middle section, it presents some highlights of this account. At the bottom, it shows the most recent interactions that this account has posted or replied to.

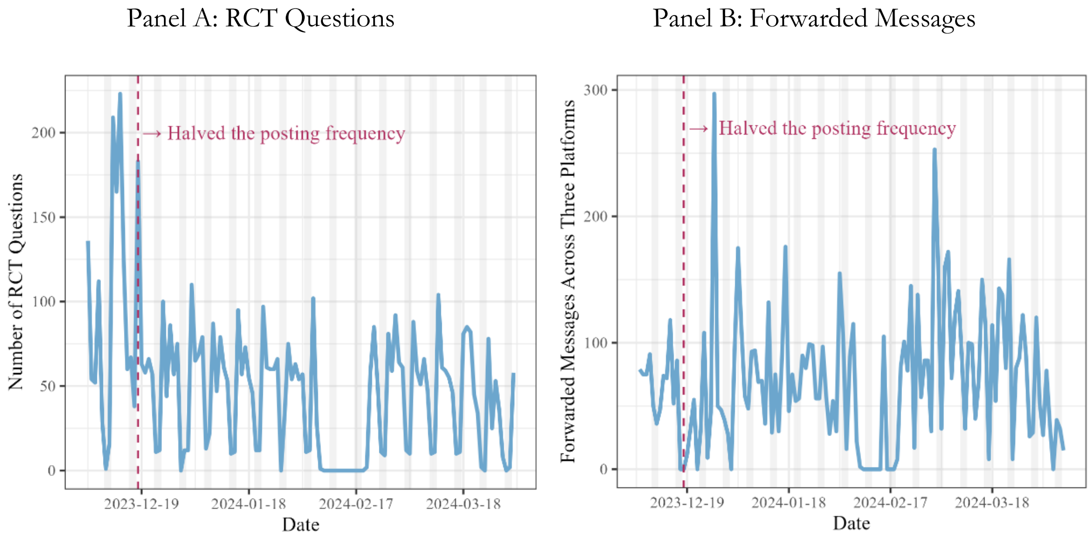


Figure A4. Frequency of RCT Questions by Day

Notes: This figure illustrates the timeline of our messages on the Q&A platform (Panel A) and the forwarded platforms (Panel B). The lines represent the number of posts approved by the platform administrators per day, and the shaded areas indicate weekends with minimal approvals. The daily fluctuations are primarily driven by censorship delays, which are independent of our experimental design. To avoid excessive delays, we halved the posting frequency two weeks into the experiment. This adjustment is unlikely to bias our results since the timing and sequence of posts were randomized before the start of the experiment.

作为一位对ESG趋势敏锐的投资者，我对您公司在可持续方面的表现感到非常好奇，也注意到您的公司在2022商道融绿ESG体系中评级为C+，远远落后于行业平均。特别关注环境领域，我很关心公司在环境方面的长期愿景，是否有减少碳排放方面的政策和计划？公司有计划提升今年的可持续报告质量吗？

irm1883277 · 2024-03-19 · 来源 网站

安 安克创新 [300866] · 2024-03-21

您好，安克创新高度重视ESG工作，于2023年6月披露上市后首份中英文版ESG报告，从“绿色产业和产品创新” “可持续运营” “负责任治理” “社区参与和发展”等多个维度展示了公司在环境、社会与治理方面的进展。截至目前，公司的商道融绿ESG最新评级为B+（2023-12-17更新，对应的ESG风险为较低风险），华证指数ESG最新评级为BBB（2024-1-31更新），Wind ESG最新评级为A（2023-6-20更新）。公司一直秉持可持续发展理念，致力于应对全球气候变化挑战，在产品和公司运营等方面采取了一系列措施，如将生物基材料/再生材料应用于产品设计、包装减塑设计、说明书无纸化、绿色低碳运营等，以推动节能减排、减少塑料使用、促进碳中和。公司《2023年可持续发展报告》也即将发布，会详细介绍公司2023年在ESG方面的进展，敬请关注。 未来，公司也将不断提升ESG治理和可持续发展报告质量，以提供更全面、更准确的信息，并持续探索科技创新与可持续发展的融合，为环境保护持续贡献力量。谢谢您的关注。

点赞

您好，我发现贵公司的万得ESG评分为BB，处于电子行业中下游。请问贵公司有无将ESG概念融入业务的具体措施？有无提高ESG评分的计划？鉴于目前年报中并未出现详细的环境相关信息披露，公司未来是否考虑增大披露力度或者发布单独的ESG报告？感谢回复

irm1885070 · 2024-03-20 · 来源 网站

富 富乐德 [301297] · 2024-03-21

公司各期半年度或年度报告中均有环境与社会责任的信息披露，敬请查询或留意。公司将对标先进，不断发展，以实际行动推动企业实现高质量发展。

点赞

投资者_1700404152000

问 :福田汽车(600166) 你好！最近在看ESG的相关资讯。我有看到贵公司在万德ESG评级体系下只有BBB,在所属行业中已经很靠后了。我想知道贵公司如何看待自身ESG表现的，以及对待董事会多样性和风险控制提升，有无具体措施？

2023年12月11日 09:21 来自 网站

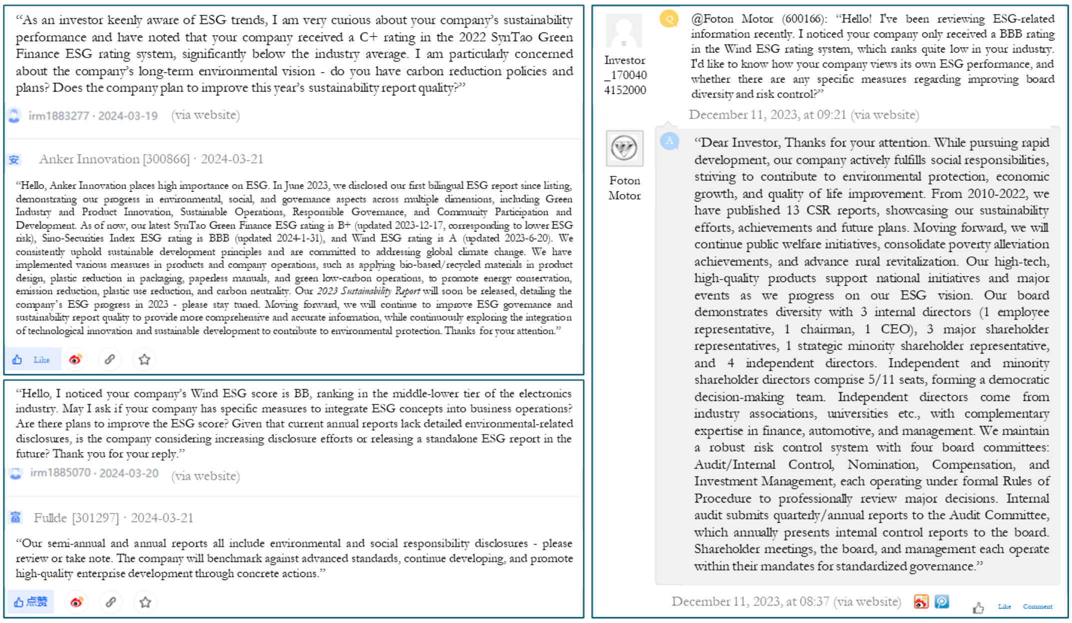
福田汽车

答 尊敬的投资者您好。感谢您的关注。公司在快速发展的同时，一直坚持自觉承担并履行社会责任，力求为保护环境、促进经济发展、提高人民生活质量贡献力量。在2010-2022 年间已累计披露了13 篇企业社会责任报告，集中展示了公司在报告期内做出的在促进经济，社会、环境及生态可持续发展方面的努力与共献，获得的荣誉和奖励以及未来展望。未来公司将一如既往的开展社会公益活动，巩固拓展脱贫攻坚成果，继续推进乡村振兴工作，以高科技、高品质产品支持国家各项事业、重大会议活动，在环境、社会责任和公司治理的履责道路上不断前行。公司董事会成员具备多样性，配置内部董事3名（其中1名为职工代表董事、1名为公司董事长、1名为总经理），大股东代表3名和战略中小股东代表1名，同时还包含了4名独立董事，中小股东董事及独立董事占比5/11，11名董事共同组成了决策民主的董事会团队。独董成员来自于行业协会、高校等，涉及财会、汽车、管理等专业领域，具备专业优势互补性。公司及董事会具有完善的风险控制体系制度。董事会下设立审计/内控委员会、提名委员会、薪酬与考核委员会、投资管理委员会4个专门委员会，分别制定了各专门委员会《议事规则》，对公司的重大决策事项以专业的角度进行审核、把关。每季度/年度公司内部审计部门向公司董事会审计/内控委员会报送季度/年度审计工作总结和计划等。审计/内控委员会每年定期向董事会提报内控报告审议。股东大会、董事会、经理层在各自职权范围内决策公司经营各事项，各司其职，规范运作。

2023年12月13日 08:37 来自 网站

收藏 | 评论

(Original)



"As an investor keenly aware of ESG trends, I am very curious about your company's sustainability performance and have noted that your company received a C+ rating in the 2022 SynTao Green Finance ESG rating system, significantly below the industry average. I am particularly concerned about the company's long-term environmental vision - do you have carbon reduction policies and plans? Does the company plan to improve this year's sustainability report quality?"

irm1883277 · 2024-03-19 (via website)

安 Anker Innovation [300866] · 2024-03-21

"Hello, Anker Innovation places high importance on ESG. In June 2023, we disclosed our first bilingual ESG report since listing, demonstrating our progress in environmental, social, and governance aspects across multiple dimensions, including Green Industry and Product Innovation, Sustainable Operations, Responsible Governance, and Community Participation and Development. As of now, our latest SynTao Green Finance ESG rating is B+ (updated 2023-12-17, corresponding to lower ESG risk), Sino-Securities Index ESG rating is BBB (updated 2024-1-31), and Wind ESG rating is A (updated 2023-6-20). We consistently uphold sustainable development principles and are committed to addressing global climate change. We have implemented various measures in products and company operations, such as applying bio-based/recycled materials in product design, plastic reduction in packaging, paperless manuals, and green low-carbon operations, to promote energy conservation, emission reduction, plastic use reduction, and carbon neutrality. Our *2023 Sustainability Report* will soon be released, detailing the company's ESG progress in 2023 - please stay tuned. Moving forward, we will continue to improve ESG governance and sustainability report quality to provide more comprehensive and accurate infomation, while continuously exploring the integration of technological innovation and sustainable development to contribute to environmental protection. Thanks for your attention."

Like

"Hello, I noticed your company's Wind ESG score is BB, ranking in the middle-lower tier of the electronics industry. May I ask if your company has specific measures to integrate ESG concepts into business operations? Are there plans to improve the ESG score? Given that current annual reports lack detailed environmental-related disclosures, is the company considering increasing disclosure efforts or releasing a standalone ESG report in the future? Thank you for your reply."

irm1885070 · 2024-03-20 (via website)

富 Fullde [301297] · 2024-03-21

"Our semi-annual and annual reports all include environmental and social responsibility disclosures - please review or take note. The company will benchmark against advanced standards, continue developing, and promote high-quality enterprise development through concrete actions."

点赞

Investor _1700404152000

Q @Foton Motor (600166): "Hello! I've been reviewing ESG-related information recently. I noticed your company only received a BBB rating in the Wind ESG rating system, which ranks quite low in your industry. I'd like to know how your company views its own ESG performance, and whether there are any specific measures regarding improving board diversity and risk control?"

December 11, 2023, at 09:21 (via website)

Foton Motor

A "Dear Investor, Thanks for your attention. While pursuing rapid development, our company actively fulfills social responsibilities, striving to contribute to environmental protection, economic growth, and quality of life improvement. From 2010-2022, we have published 13 CSR reports, showcasing our sustainability efforts, achievements and future plans. Moving forward, we will continue public welfare initiatives, consolidate poverty alleviation achievements, and advance rural revitalization. Our high-tech, high-quality products support national initiatives and major events as we progress on our ESG vision. Our board demonstrates diversity with 3 internal directors (1 employee representative, 1 chairman, 1 CEO), 3 major shareholder representatives, 1 strategic minority shareholder representative, and 4 independent directors. Independent and minority shareholder directors comprise 5/11 seats, forming a democratic decision-making team. Independent directors come from industry associations, universities etc., with complementary expertise in finance, automotive, and management. We maintain a robust risk control system with four board committees: Audit/Internal Control, Nomination, Compensation, and Investment Management, each operating under formal Rules of Procedure to professionally review major decisions. Internal audit submits quarterly/annual reports to the Audit Committee, which annually presents internal control reports to the board. Shareholder meetings, the board, and management each operate within their mandates for standardized governance."

December 11, 2023, at 08:37 (via website)

Like Comment

(English Translation)

Figure A5. Examples of Q&A Interactions in the RCT

Notes: This figure presents screenshots of three examples of our Q&A interactions with firms during the experiment. The texts in the upper regions are our questions, and the texts in the lower regions are firms' responses. Three points are worth mentioning: First, our questions are tailored to each firm's actual ESG performance by citing their rating results and identifying areas for improvement. Second, despite differing content, our questions are phrased with similar lengths and sentiments to minimize noise. Third, firms provide drastically different responses in terms of length, content, and sentiment. The two left examples show relatively shorter and more qualitative responses, while the right example includes numerous statistics and specific actions.

Panel A: Within-Firm Similarity

Panel B: Between-Firm Similarity

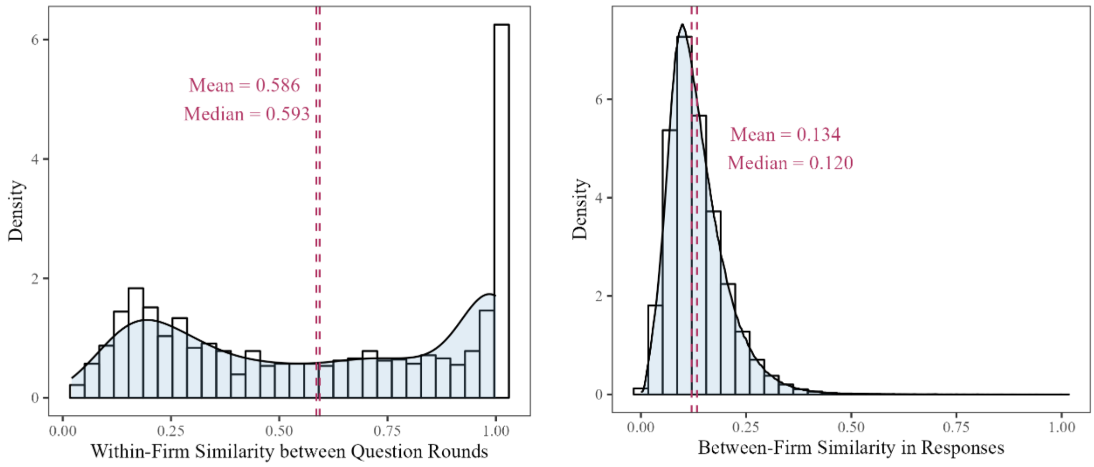


Figure A6. Similarity of Firms' Online Responses

Notes: This figure displays kernel density plots of pairwise cosine similarity measures for firms' textual responses. Panel A shows within-firm similarity, comparing each firm's responses to the first-round RCT questions with its subsequent-round responses. Panel B presents between-firm similarity for first-round responses across the sample. Vertical maroon dashed lines indicate the mean and median similarity values in each panel.

Panel A: Response Length and ESG Performance

Panel B: Response Sentiment and ESG Performance

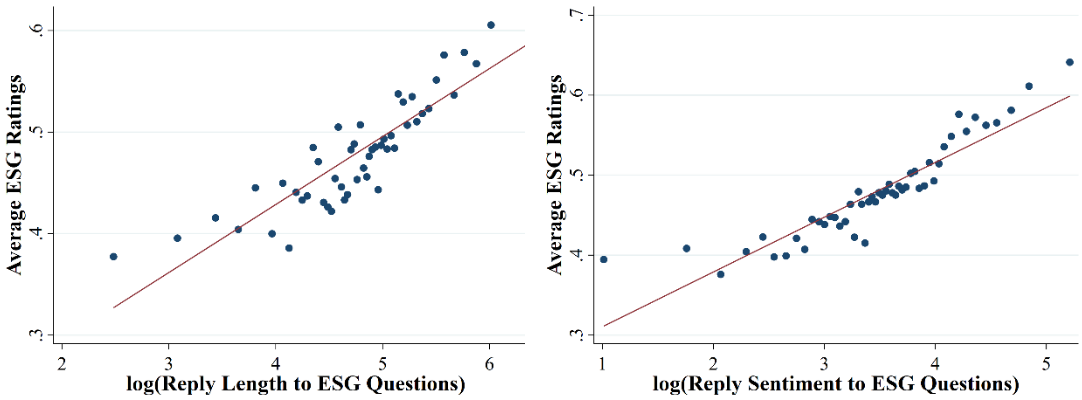


Figure A7. Correlation between Firms' Response Quality and ESG Performance

Notes: This figure consists of two binned scatterplots of the relationship between firms' response quality to ESG-related questions and their actual ESG performance. The response quality is measured by the log of reply length (number of Chinese characters) and reply sentiment derived from sentiment analysis. The actual ESG performance is measured using the average standardized ESG ratings from multiple agencies. The standardization is based on the percentile ranking of a firm according to each ESG rating agency.

投资者_1709603244000

:首旅酒店(600258)集团已发布预赢公告，但股价节后却与大盘稳步上升趋势出现明显背离，是否代表公告与事实不符导致市场信心不足

2024年03月05日 13:05 来自 网站

首旅酒店

公司始终把做好企业经营作为价值创造的核心，做大做强主业，2023年继续推进“发展为先、产品为王、会员为本、效率赋能”四大核心经营战略，紧抓酒店市场强劲复苏机遇，实现同比大幅扭亏为盈；并且重视可持续发展和股东的长远利益，贯彻高质量发展理念在国内同行业率先实施ESG治理。同时，公司围绕价值实现不断深化资本市场形象，全方位做好信息披露和投资者交流，提升电话、电子邮件、“上证e互动”、股东大会等互动交流效率，倡导价值投资理念。从而，持续提升业绩，回报投资者。感谢您对公司的关注！

2024年03月06日 11:39 来自 网站

收藏 | 评论

(Original)

Investor_1709602244000

@BTG HOMEINNS Hotels (Group) Co., Ltd. (600258): “The company has issued a preliminary earnings announcement, but the stock price has noticeably diverged from the broader market’s steady upward trend. Does this indicate a discrepancy between the announcement and actual performance, leading to a lack of market confidence?”

March 5, 2024, at 13:05 (via website)

BTG HOMEINNS Hotels (Group) Co., Ltd.

“The company has always prioritized strong business operations as the core of value creation, focusing on expanding and strengthening its main business. In 2023, we continued to advance our four core operational strategies: “development first, product focus, member-centric, and efficiency-driven.” We seized the opportunity of a robust recovery in the consumer market, achieving a significant year-on-year turnaround from losses to profitability. Additionally, we emphasize sustainable development and the long-term interests of shareholders, implementing high-quality development principles and pioneering ESG governance in the domestic industry. Simultaneously, the company has deepened its capital market presence by enhancing information disclosure and investor communication. We have improved interaction efficiency through channels such as phone calls, emails, the “Shanghai e-Interaction” platform, and shareholder meetings, promoting value investment principles. These efforts aim to consistently improve performance and deliver returns to investors. Thank you for your attention to the company!”

March 6, 2024, at 11:39 (via website)

Like | Comment

(English Translation)

Figure A8. Examples of Firms’ Answer Spillovers

Notes: This figure illustrates an example of firms’ answer spillovers. In the screenshot, an investor questions whether the divergence between the company’s stock price and the broader market trend following a pre-earnings announcement indicates insufficient or inconsistent information. In its response, the firm not only discusses its operational strategies and strong financial turnaround but also emphasizes its commitment to ESG governance and sustainable development. This example demonstrates how firms may reference their ESG performance when answering questions unrelated to ESG, a phenomenon we define as “answer spillovers.”

Figure A9. Examples of Investors’ Question Spillovers

Notes: This figure presents two representative examples of investors’ question spillovers. In the treated firm case, an investor questions whether the firm evaluates partners’ ESG performance and plans to disengage with poor ESG performers. The firm responds by emphasizing its ESG commitments and intent to collaborate with high-ESG partners. In the control firm case, an investor asks about CSR rating concerns during financing. The firm reports no CSR-related inquiries while reaffirming its ESG commitments. Both cases demonstrate emergent investor ESG engagement absent pre-treatment, a pattern we classify as “question spillovers.”

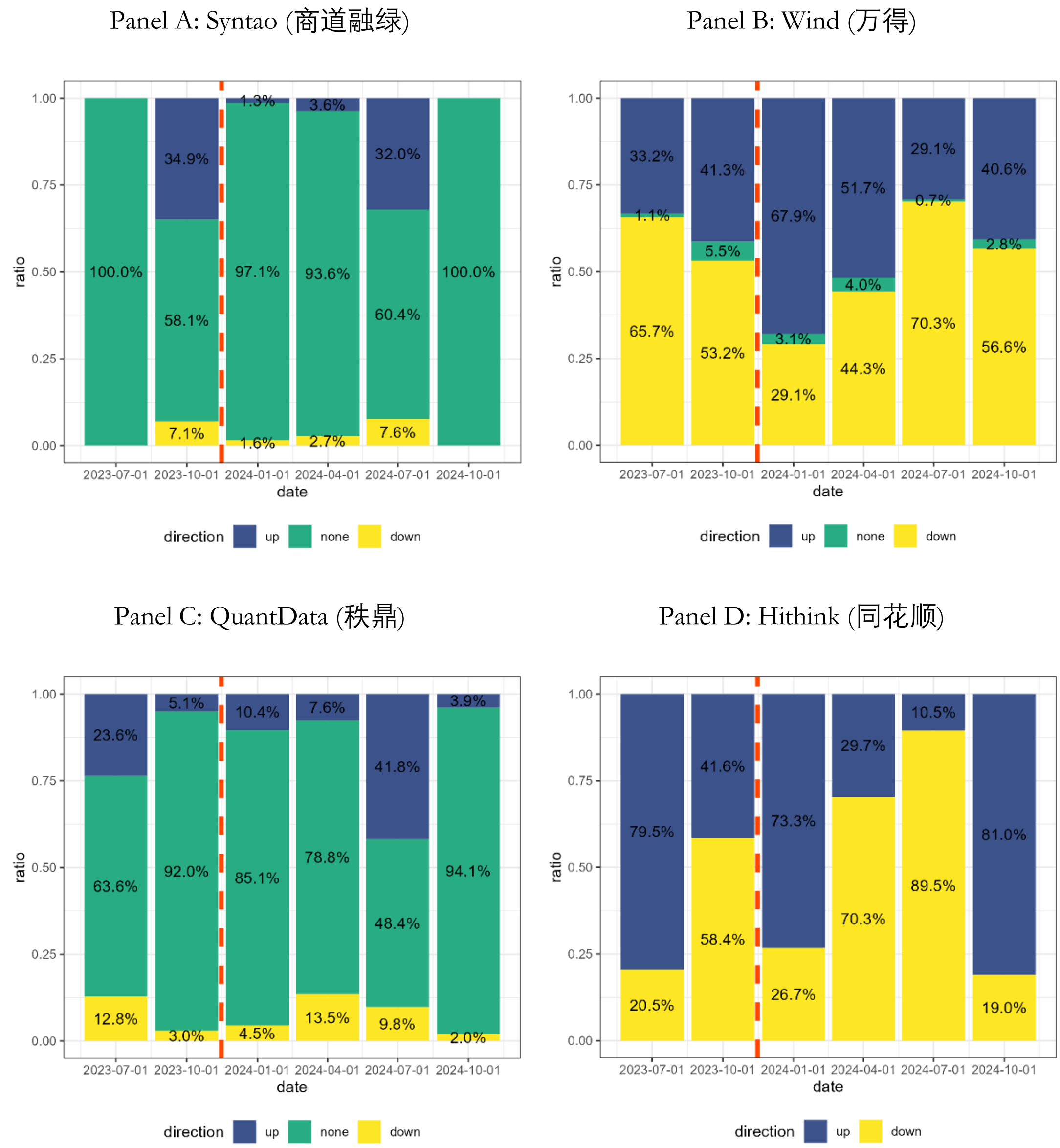


Figure A10. Update Frequency of ESG Ratings

Notes: This figure displays the update frequency of each ESG rating agency, categorized by the direction of rating adjustment (up, down, or no adjustment). Panel A and Panel C pertain to agencies with categorical ratings, while the other panels pertain to agencies with continuous ratings. The red dotted line marks the division between the pre- and post-experiment periods. The black numbers indicate the percentages of firms in our experiment that experience rating adjustments each quarter. Rating agencies conduct large-scale updates to their results primarily in July, following the release of annual reports and ESG reports by most firms.

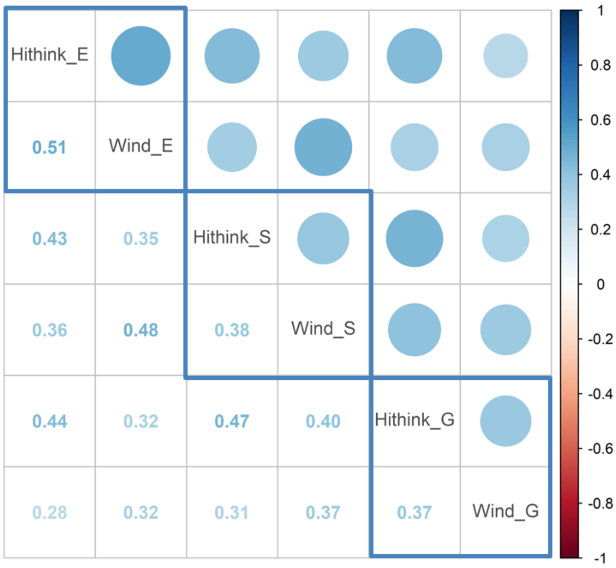
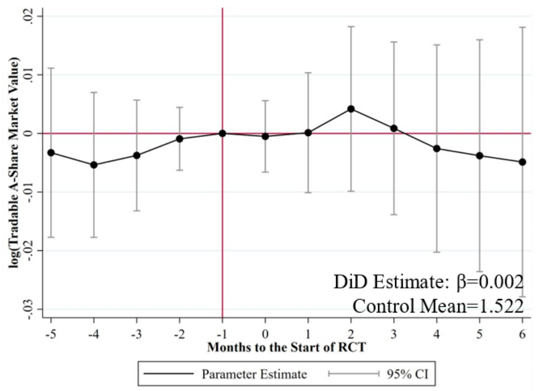


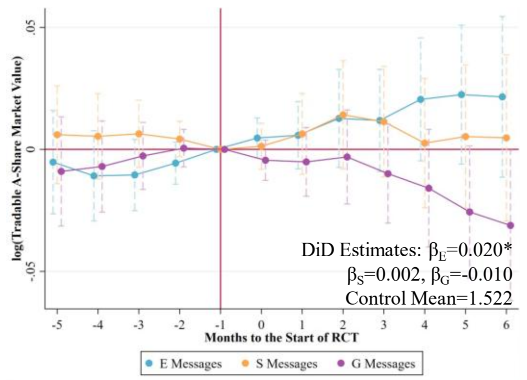
Figure A11. Correlation of E/S/G Ratings Across Rating Agencies

Notes: This figure displays correlation matrices of firm-level E, S, and G ratings from Wind and Hithink. Ratings show the strongest inter-agency agreement on environmental (E) dimensions, followed by social (S) and governance (G) measures. This pattern aligns with evidence in Berg et al. (2022) and suggests that environmental performance is more observable and verifiable by third parties, while governance attributes exhibit greater subjectivity.

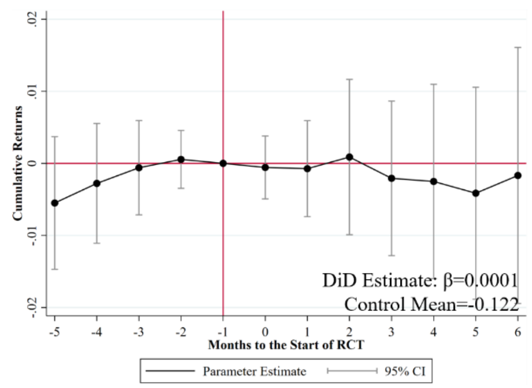
Panel A: Aggregate Effect on Market Value



Panel B: Heterogenous Effect on Market Value



Panel C: Aggregate Effect on Cumulative Returns



Panel D: Heterogenous Effect on Cumulative Returns

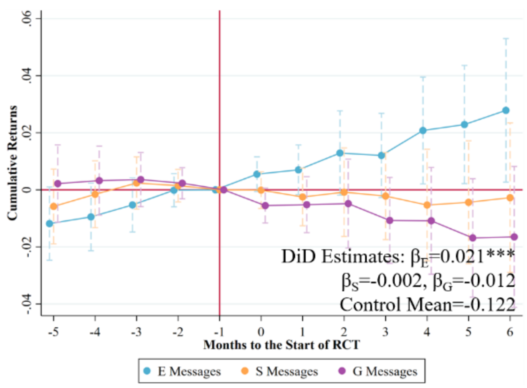


Figure A12. Trends of Alternative Market Response Measures

Notes: This figure presents estimates of dynamic treatment effects on alternative market response measures, estimated using Equation (4) and Equation (8). Panels A and B show results where the dependent variable is the natural logarithm of daily tradable A-share market valuation at the firm level. Panels C and D show results where the dependent variable is cumulative returns to each stock since the beginning of the data collection period. Left panels (A and C) measure aggregate treatment effects using interaction terms between period and treat dummies. Right panels (B and D) measure group-specific treatment effects using interaction terms between period and treatment arm dummies. Dots represent regression estimates, and error bars indicate 95% confidence intervals. Standard errors are clustered at the firm level to address potential serial correlation. The corresponding regression estimates are reported in Table A9.

Panel A: Productivity Panel B: Transparency

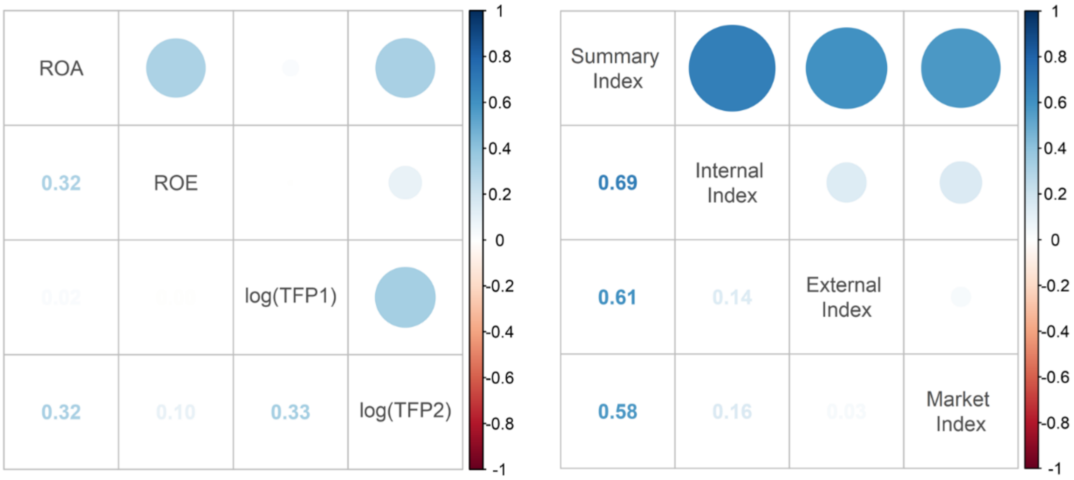
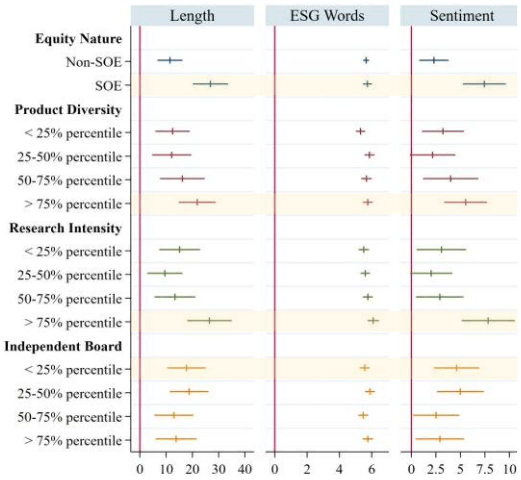


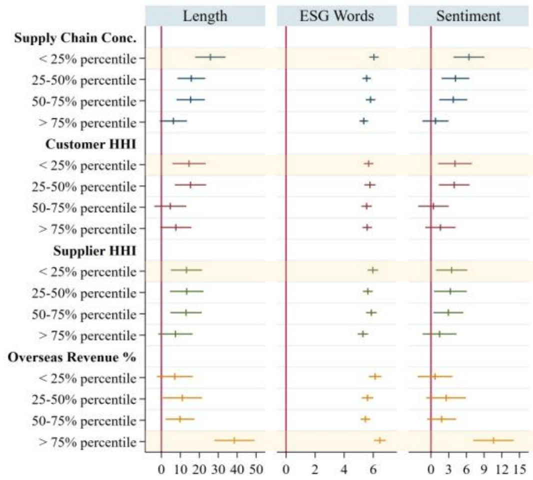
Figure A13. Correlation of Firm Productivity and Transparency Measures

Notes: This figure presents correlation matrices for firms' productivity and transparency measures. Panel A reveals weak pairwise correlations among the four productivity proxies, consistent with the fundamental challenge of observing firms' true productivity. Panel B reveals that the three transparency sub-indices (internal governance, external relationships, and market information) exhibit limited intercorrelations but contribute roughly equally to the summary index, as expected given our z-score standardization approach. The orthogonal patterns across both panels indicate that these measures capture distinct facets of firm performance and information environments, providing multiple independent channels for testing our theoretical predictions.

Panel A: Internal Management Index



Panel B: External Relationship Index



Panel C: Market Research Index

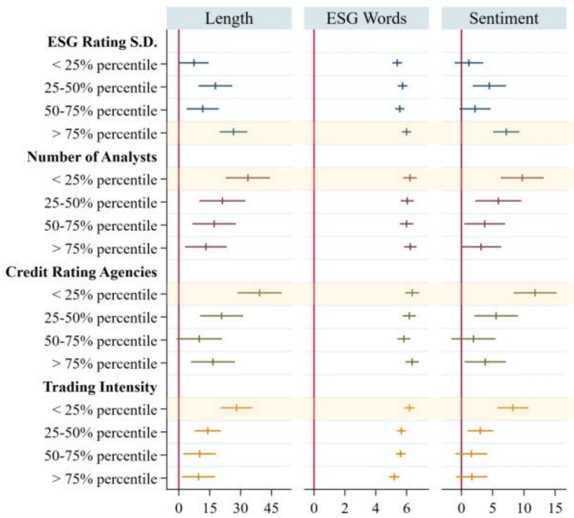


Figure A14. Heterogeneity of Responses Across Transparency Indicators

Notes: This figure presents the heterogeneity results for the indicators that make up the three transparency indices, estimated from Equation (6). All indicators are continuous and divided into four quartiles, except for equity nature, which is a dummy variable indicating whether a firm is a state-owned enterprise. Each dot represents a regression estimate, with error bars denoting 95% confidence intervals. The highlighted quartile groups are those expected to exhibit the largest effects according to our conceptual framework.

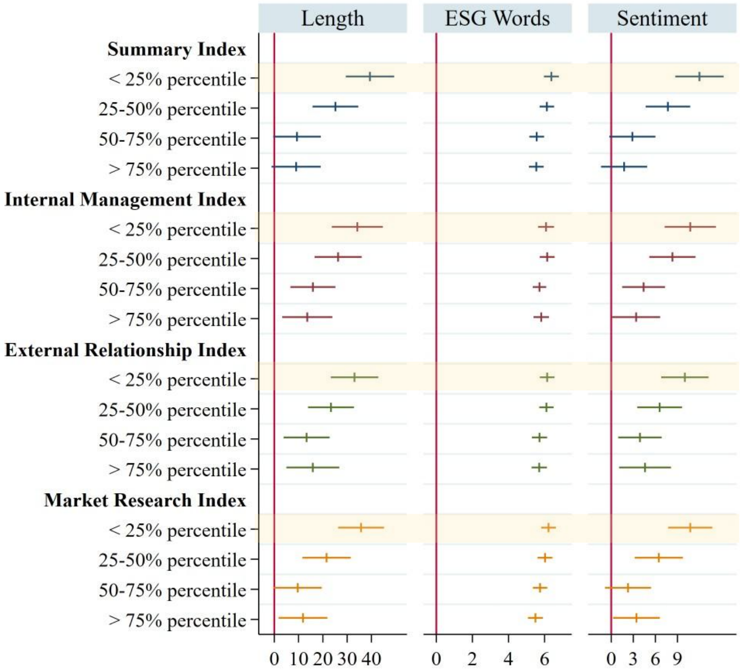
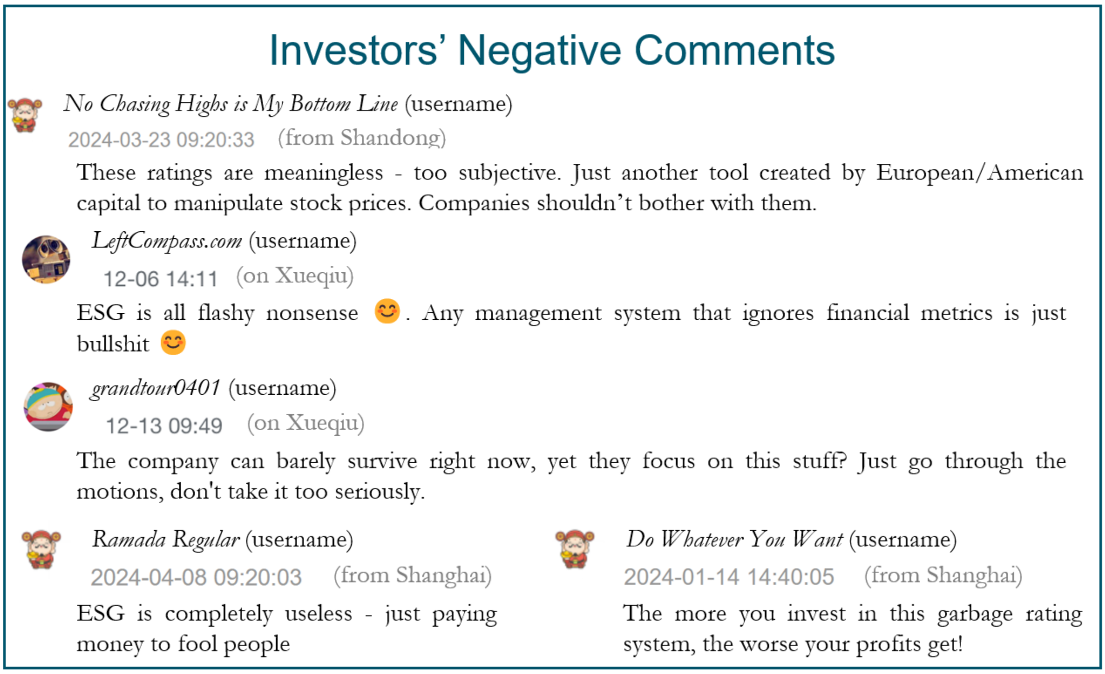


Figure A15. Robustness of Responses Heterogeneity after Controlling for ROA

Notes: This figure examines the robustness of firms' response heterogeneity across transparency levels when controlling for ROA quartiles in Equation (6). Building on the regressions from Panel 2 of Figure 8, we include interaction terms between experiment questions and ROA quartiles, as well as between ROA quartiles and day dummies. The figure illustrates the remaining variation captured by the interaction terms between experiment questions and transparency quartiles. Each dot represents a regression estimate, with error bars denoting 95% confidence intervals. The highlighted quartile groups are those expected to exhibit the largest effects according to our conceptual framework.

(Original)



(English Translation)

Figure A16. Examples of Negative Investor Comments

Notes: This figure shows five representative negative comments toward our ESG messages on the investor forums. The first, fourth, and fifth examples come from Guba, and the second and third examples come from Xueqiu. The comments reveal retail investors' skepticism toward ESG's practical value, with some dismissing it as "meaningless" or "useless" and others explicitly prioritizing financial returns over ESG considerations. These patterns suggest that firms may face dual pressures when pursuing ESG strategies in markets where retail investors challenge their legitimacy or relevance to financial performance.

Panel A: Cultural Factors Based on Headquarters (Full Sample)

Panel B: Cultural Factors Based on Headquarters (First-Tier Cities Excluded)

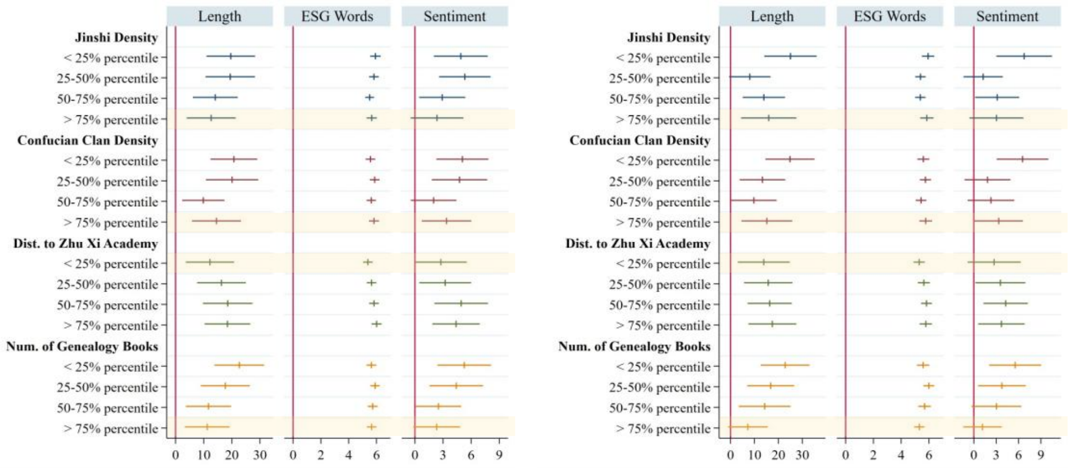


Figure A17. Heterogeneity of Responses Across Alternative Cultural Factors

Notes: This figure shows the heterogeneity results for firms' online responses based on cultural factors of their headquarters locations, estimated using Equation (6). Panel A includes all firms with available headquarter information, while Panel B excludes observations from four first-tier cities (Beijing, Shanghai, Shenzhen, and Guangzhou) where 27% of headquarters are concentrated, ensuring results are not driven by these metropolitan areas. All indicators are continuous and divided into four quartiles. Each dot represents a regression estimate, with error bars indicating 95% confidence intervals. The highlighted quartile groups are those expected to exhibit the largest effects according to values-driven motivations.

Table A1. Firms' Aggregate Online Responses

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	Length	Sentiment	ESG Words	E Words	S Words	G Words	Forward-Looking Words	Numbers	Names	Boilerplate	Accounting Words	Regulation Words
Treat	16.089***	3.841***	5.679***	1.751***	1.296***	0.771***	0.277***	-0.604***	-0.649***	3.247***	-0.372***	2.365***
	(2.064)	(0.657)	(0.079)	(0.049)	(0.025)	(0.020)	(0.023)	(0.067)	(0.102)	(0.385)	(0.030)	(0.052)
Control Mean	75.946	23.615	0.193	0.092	0.008	0.090	0.312	1.558	1.769	24.435	1.005	0.576
Observations	144,872	144,872	144,872	144,872	144,872	144,872	144,872	144,872	144,872	144,872	144,872	144,872
R-Squared	0.308	0.300	0.556	0.291	0.462	0.268	0.183	0.203	0.184	0.333	0.294	0.270
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry-Day FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: This table reports average treatment effect estimates of our experiment on firms' online responses on Q&A platforms based on Equation (1). The dependent variables include four categories of response quality metrics. The first category comprises basic textual features, including response length (measured by the number of Chinese characters), ESG (and E/S/G) keyword counts, and answer sentiment. The second category, numbers and names, quantifies the density of quantitative information (dates, times, ordinals, cardinals, quantities, percentages, and monetary values) and named entities (organizations, products, locations, and persons) identified using SpaCy's Named Entity Recognition (NER) tool (Lin et al., 2024), normalized by total word count. The third category measures boilerplate language, defined as the proportion of generic words detected using phrase-matching methods from Lang and Stice-Lawrence (2015). The final category evaluates thematic content, including forward-looking, accounting, and regulatory language shares, calculated via normalized counts of dictionary terms from Bozanic et al. (2018) and Muslu et al. (2015). The independent variable is a binary indicator for whether a specific question belongs to one of our treatment arms. All regressions control for question length and sentiment and include firm and industry-by-day fixed effects. Standard errors in parentheses are clustered at the firm level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table A2. Heterogeneity of Online Responses Across Treatment Timing

	(1)	(2)	(3)	(4)	(5)	(6)
	Length	Sentiment	ESG Words	E Words	S Words	G Words
Early Treatment	19.305***	5.527***	5.787***	1.949***	1.317***	0.638***
	(3.195)	(1.002)	(0.123)	(0.084)	(0.041)	(0.026)
Late Treatment	20.173***	4.358***	5.711***	1.768***	1.362***	0.946***
	(2.955)	(0.958)	(0.120)	(0.072)	(0.038)	(0.036)
Control Mean	75.551	23.504	0.189	0.089	0.008	0.090
Observations	142,458	142,458	142,458	142,458	142,458	142,458
R-Squared	0.305	0.298	0.475	0.260	0.398	0.232
P Value: Early=Late	0.837	0.384	0.657	0.102	0.419	0.000
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry-Day FE	Yes	Yes	Yes	Yes	Yes	Yes

Notes: This table presents regression estimates of firms' online responses across treatment timing based on Equation (6). The dependent variables include response length (measured by the number of Chinese characters), the number of ESG (and E/S/G) keywords in answers, and response sentiment. The independent variables include two dummies: early treatment refers to questions from treatment arms asked before the median experiment date; late treatment refers to questions from treatment arms asked after the median experiment date. We exclude 2+ rounds of questions to ensure the clean identification of timing effects. Control variables include question length and sentiment. The p-values are derived from pairwise t-tests comparing the coefficients of early treatment against late treatment. All regressions include firm and industry-by-day fixed effects. Standard errors in parentheses are clustered at the firm level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table A3. Heterogeneity of Online Responses Across Experimental Rounds

	(1)	(2)	(3)	(4)	(5)	(6)
	Length	Sentiment	ESG Words	E Words	S Words	G Words
First Round of RCT Messages	20.281***	5.109***	5.751***	1.860***	1.337***	0.785***
	(2.240)	(0.715)	(0.086)	(0.055)	(0.028)	(0.023)
2+ Round of RCT Messages	11.553***	2.468***	5.601***	1.633***	1.252***	0.756***
	(2.447)	(0.774)	(0.095)	(0.058)	(0.030)	(0.025)
Control Mean	75.920	23.607	0.193	0.091	0.008	0.090
Observations	144,872	144,872	144,872	144,872	144,872	144,872
R-Squared	0.308	0.300	0.556	0.292	0.463	0.268
P Value: R1=R2	0.000	0.000	0.084	0.000	0.003	0.253
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry-Day FE	Yes	Yes	Yes	Yes	Yes	Yes

Notes: This table presents regression estimates of firms' online responses across experimental rounds based on Equation (6). The dependent variables include response length (measured by the number of Chinese characters), the number of ESG (and E/S/G) keywords in answers, and response sentiment. The independent variables are dummies for whether a question belongs to the first or later rounds of our experiment, which measure the round-specific average treatment effects. The p-values are derived from pairwise t-tests comparing the coefficients of the first round against later rounds. Control variables include question length and sentiment. All regressions include firm and industry-by-day fixed effects. Standard errors in parentheses are clustered at the firm level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table A4. Heterogeneity of Online Responses Across Q&A Platforms

	(1)	(2)	(3)	(4)	(5)	(6)
	Length	Sentiment	ESG Words	E Words	S Words	G Words
Treatment on the Shenzhen Platform	14.371***	3.230***	5.473***	1.712***	1.320***	0.793***
	(2.614)	(0.823)	(0.103)	(0.062)	(0.035)	(0.028)
Treatment on the Shanghai Platform	17.613***	4.382***	5.861***	1.786***	1.275***	0.752***
	(2.907)	(0.937)	(0.118)	(0.075)	(0.036)	(0.029)
Control Mean	75.936	23.611	0.192	0.092	0.008	0.090
Observations	144,872	144,872	144,872	144,872	144,872	144,872
R-Squared	0.308	0.300	0.556	0.292	0.462	0.268
P Value: SZ=SH	0.383	0.332	0.014	0.441	0.366	0.308
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry-Day FE	Yes	Yes	Yes	Yes	Yes	Yes

Notes: This table presents regression estimates of firms' online responses across Q&A platforms based on Equation (6). The dependent variables include response length (measured by the number of Chinese characters), the number of ESG (and E/S/G) keywords in answers, and response sentiment. The independent variables are dummies for whether a treated question is asked on the Shenzhen (SZ) or Shanghai (SH) Q&A platform, respectively. The p-values are derived from pairwise t-tests comparing the coefficients of the SZ platform against the SH platform. Control variables include question length and sentiment. All regressions include firm and industry-by-day fixed effects. Standard errors in parentheses are clustered at the firm level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table A5. Firms' Answer Spillovers and Investors' Question Spillovers

	(1) Answer Spillovers	(2) Question Spillovers
Post * Treat	0.018**	0.077***
	(0.009)	(0.027)
Control Mean	0.265	0.080
Observations	1,239,795	1,327,167
R-Squared	0.736	0.554
Firm FE	Yes	Yes
Industry-Day FE	Yes	Yes

Notes: This table reports treatment effect estimates for ESG-related spillover behavior based on Equation (2). Column (1) examines firms' response patterns, where the dependent variable is the cumulative ratio of ESG keywords in firms' answers to total words across all responses. This measure captures the relative emphasis placed on ESG topics by treated versus control firms. Column (2) analyzes investor behavior, with the dependent variable defined as the cumulative ratio of ESG-related questions directed at treated versus control firms, reflecting heightened investor interest following our intervention. The key independent variable in both specifications is the interaction term between post and treat dummies to measure the average treatment effect. Both regressions include firm fixed effects and industry-by-day fixed effects. Standard errors in parentheses are clustered at the firm level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table A6. Firms' Aggregate Offline Actions

	ESG Ratings				ESG Report	Communications	Negative Media Reports	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Syntao	Wind	QuantData	Hithink	Release Dummy	Mention ESG	Regulation Violations	Supply Chain Issues
Post * Treat	1.045*	0.188	0.475	0.147	2.754***	1.948***	-0.166	-0.044
	(0.599)	(0.160)	(0.343)	(0.096)	(1.017)	(0.735)	(0.135)	(0.045)
Control Mean	45.141	59.159	49.213	63.810	25.104	1.504	0.731	0.152
Observations	32,946	33,038	32,751	33,170	33,894	11,458	1,324,596	1,324,596
R-Squared	0.815	0.815	0.863	0.920	0.754	0.660	0.025	0.021
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	No	No	No	No	Yes	No	No	No
Quarter FE	Yes	Yes	Yes	Yes	No	No	No	No
Industry-Day FE	No	No	No	No	No	Yes	Yes	Yes

Notes: This table reports average treatment effect estimates of our experiment on firms' offline ESG-related actions based on Equations (2) and (3). The dependent variables include quarterly ESG ratings from cited and uncited agencies, the release of ESG reports, mentions of ESG during institutional investor communications, and ESG-related negative media coverage. All dependent variables are scaled by 100 to improve coefficient readability. The independent variable is the interaction term between post and treat dummies to measure the average treatment effect. Specifications for yearly and quarterly data include firm and year or quarter fixed effects, while daily analyses incorporate firm and industry-by-day fixed effects. The first two columns additionally control for propensity scores of the agency being cited by our experiment. Standard errors in parentheses are clustered at the firm level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table A7. Firms' ESG Report Quality

	(1) Sentence Length	(2) Transition Words	(3) Rare Words	(4) Fog Index	(5) Numbers	(6) Names	(7) Boilerplate	(8) Forward-Looking Words	(9) Accounting Words	(10) Regulation Words
Post * Treat	-3.073	-0.166	-0.306	-0.739	0.005	-0.036	-0.007	-0.080	-0.116	0.237
	(15.560)	(0.130)	(0.240)	(1.437)	(0.053)	(0.041)	(0.286)	(0.326)	(0.323)	(0.478)
Control Mean	104.063	3.174	0.788	13.915	4.029	2.461	9.179	19.508	19.457	36.585
Observations	8,043	8,043	8,043	8,043	8,043	8,043	8,043	8,043	8,043	8,043
R-Squared	0.452	0.574	0.457	0.334	0.634	0.686	0.669	0.588	0.697	0.614
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: This table reports regression estimates of firms' ESG report quality based on Equation (3). The dependent variables comprise four categories. The first four columns are standard textual readability metrics, including the average sentence length, transition word (adverbs and conjunctions) density, rare word density, and the Fog Index (Li, 2008). The next two columns, numbers and names, quantify the density of quantitative information (dates, times, ordinals, cardinals, quantities, percentages, and monetary values) and named entities (organizations, products, locations, and persons) identified using SpaCy's Named Entity Recognition (NER) tool (Lin et al., 2024). Both measures are normalized by total word count. The seventh column, boilerplate, identifies standardized disclosures that are too generic to be informative (Lang & Stice-Lawrence, 2015). We compute this by (1) extracting all common phrases from the full corpus of firms' ESG reports and (2) calculating the percentage of sentences containing these boilerplate phrases. The last three columns (forward-looking words, accounting words, and regulation words) are derived from established NLP dictionaries in the literature (Bozanic et al., 2018; Muslu et al., 2015). For each, we count relevant phrase occurrences and normalize them by total sentence count. The independent variable is the interaction term between post and treat dummies to measure the average treatment effect. All regressions include firm and year fixed effects. Standard errors in parentheses are clustered at the firm level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table A8. Mentions of ESG During Investor Communications by Source

	Communications – Mention ESG		
	(1)	(2)	(3)
	All	Investors' Questions	Firms' Answers
Post * Treat	1.948***	0.204	1.586***
	(0.735)	(0.394)	(0.596)
Control Mean	1.504	0.451	0.715
Observations	11,458	11,418	11,412
R-Squared	0.660	0.601	0.604
Firm FE	Yes	Yes	Yes
Industry-Day FE	Yes	Yes	Yes

Notes: This table reports regression estimates of mentions of ESG during institutional investor communications based on Equation (2). The dependent variable is a set of dummy variables indicating whether ESG keywords were mentioned (1) throughout the communication, (2) in investors' questions, or (3) in firms' answers. All dependent variables are scaled by 100 to improve coefficient readability. Column 1 replicates the results in Column 6 of Table 3, while Columns 2 and 3 separately analyze ESG keyword mentions in questions and answers from the communication transcripts. The independent variable is the interaction term between post and treat dummies to measure the average treatment effect. All regressions include firm fixed effects and industry-by-day fixed effects. Standard errors in parentheses are clustered at the firm level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table A9. Aggregate and Heterogeneous Market Responses

	Log(Tradable A-Share Market Price)		Log(Tradable A-Share Market Value)		Cumulative Returns	
	(1)	(2)			(5)	(6)
Post * Treat	0.000		0.002		0.000	
	(0.005)		(0.008)		(0.005)	
Post * (ESG Messages)		-0.006		-0.006		-0.006
		(0.008)		(0.010)		(0.008)
Post * (E Messages)		0.022***		0.020*		0.021***
		(0.008)		(0.011)		(0.008)
Post * (S Messages)		-0.002		0.002		-0.002
		(0.008)		(0.011)		(0.008)
Post * (G Messages)		-0.013		-0.010		-0.012
		(0.008)		(0.010)		(0.008)
Control Mean	2.517	2.517	1.522	1.522	-0.122	-0.122
Observations	1,164,510	1,164,510	1,164,510	1,164,510	1,164,510	1,164,510
R-squared	0.978	0.978	0.973	0.973	0.695	0.696
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry-Day FE	Yes	Yes	Yes	Yes	Yes	Yes
Firm Clusters	Yes	Yes	Yes	Yes	Yes	Yes

Notes: This table presents aggregate and heterogeneous treatment effect estimates of stock market responses based on Equation (2) and (7). The first two columns show our main dependent variable: the natural logarithm of daily tradable A-share closing prices at the firm level. Columns 3-6 show additional market response measures using the natural logarithm of daily tradable A-share market capitalization and cumulative returns. Odd-numbered columns report the average treatment effect using the interaction between post and treat dummies. Even-numbered columns report group-specific average treatment effects using interactions between post-treatment indicators and treatment arm dummies. The estimation window is July 2023 through June 2024. All regressions include firm fixed effects and industry-by-day fixed effects. Standard errors in parentheses are clustered at the firm level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table A10. Heterogeneity of Firms' Online Responses Across Treatments

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	Length	Sentiment	ESG Words	E Words	S Words	G Words	Forward-Looking Words	Numbers	Names	Boilerplate	Accounting Words	Regulation Words
ESG Messages	6.028*	1.745	5.440***	1.483***	1.211***	0.690***	0.330***	-0.790***	-0.645***	4.286***	-0.341***	2.188***
	(3.335)	(1.098)	(0.143)	(0.070)	(0.043)	(0.034)	(0.043)	(0.112)	(0.204)	(0.683)	(0.046)	(0.095)
E Messages	25.946***	6.030***	6.461***	3.216***	1.036***	0.554***	0.321***	-0.300**	-0.859***	1.665**	-0.496***	2.190***
	(3.679)	(1.142)	(0.183)	(0.144)	(0.041)	(0.036)	(0.043)	(0.123)	(0.161)	(0.687)	(0.048)	(0.095)
S Messages	21.421***	5.640***	5.574***	1.272***	1.772***	0.649***	0.248***	-0.652***	-0.656***	3.482***	-0.400***	2.499***
	(4.234)	(1.352)	(0.152)	(0.066)	(0.064)	(0.033)	(0.043)	(0.121)	(0.161)	(0.707)	(0.052)	(0.100)
G Messages	11.038***	1.908	5.225***	1.009***	1.156***	1.221***	0.203***	-0.671***	-0.422**	3.524***	-0.247***	2.601***
	(4.019)	(1.291)	(0.147)	(0.056)	(0.045)	(0.051)	(0.048)	(0.115)	(0.211)	(0.736)	(0.064)	(0.120)
Control Mean	76.006	23.629	0.194	0.092	0.010	0.090	0.312	1.559	1.769	24.430	1.004	0.577
Observations	144,872	144,872	144,872	144,872	144,872	144,872	144,872	144,872	144,872	144,872	144,872	144,872
R-Squared	0.308	0.300	0.558	0.316	0.477	0.277	0.183	0.203	0.184	0.333	0.294	0.271
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry-Day FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: This table reports heterogeneous treatment effects across experimental arms for firms' responses on Q&A platforms, estimated using Equation (6). The dependent variables mirror those in Table A1. The independent variables are dummies indicating whether a question belongs to each of our treatment arms to capture group-specific average treatment effects. All regressions control for question length and sentiment and include firm and industry-by-day fixed effects. Standard errors in parentheses are clustered at the firm level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table A11. Heterogeneity of Firms' Offline Actions Across Treatments

	ESG Ratings				ESG Report	Communications	Negative Media Reports	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Syntao	Wind	QuantData	Hithink	Release Dummy	Mention ESG	Regulation Violations	Supply Chain Issues
Post * (ESG Messages)	1.439	0.172	0.500	-0.059	2.440	0.685	-0.153	-0.005
	(0.971)	(0.224)	(0.518)	(0.141)	(1.518)	(1.015)	(0.200)	(0.049)
Post * (E Messages)	0.880	0.142	0.843*	0.347**	3.497**	2.228**	-0.174	-0.105
	(1.165)	(0.235)	(0.507)	(0.144)	(1.529)	(1.047)	(0.174)	(0.072)
Post * (S Messages)	0.932	0.259	0.491	0.158	2.109	1.762	-0.088	-0.073
	(1.196)	(0.227)	(0.509)	(0.147)	(1.505)	(1.089)	(0.154)	(0.063)
Post * (G Messages)	0.722	0.162	0.057	0.142	2.975*	3.161***	-0.250	0.009
	(1.018)	(0.238)	(0.497)	(0.143)	(1.536)	(1.186)	(0.228)	(0.066)
Control Mean	45.141	59.159	49.213	63.811	25.104	1.497	0.731	0.152
Observations	32,946	33,038	32,751	33,170	33,894	11,458	1,324,596	1,324,596
R-Squared	0.815	0.815	0.863	0.920	0.754	0.660	0.025	0.021
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	No	No	No	No	Yes	No	No	No
Quarter FE	Yes	Yes	Yes	Yes	No	No	No	No
Industry-Day FE	No	No	No	No	No	Yes	Yes	Yes

Notes: This table presents heterogeneous treatment effect estimates across experimental arms on firms' offline ESG-related actions, employing Equation (7) specifications with varying fixed effects tailored to data frequency. The dependent variables include quarterly ESG ratings, release of ESG reports, mentions of ESG in institutional investor communications, and ESG-related negative media coverage, all scaled by 100 for interpretability. The independent variable is an interaction term between post-treatment indicators and treatment arm dummies, capturing group-specific average treatment effects. Specifications for yearly and quarterly data include firm and year-quarter fixed effects, while daily analyses incorporate firm and industry-by-day fixed effects. The first two columns additionally control for propensity scores of the agency being cited by our experiment. Standard errors in parentheses are clustered at the firm level. *** $p < 0.01$, **$p < 0.05$, *$p < 0.1$.

Table A12. Heterogeneity of Investors' Responses Across Treatments

	(1) ESG Question Spillovers	(2) General Question Sentiment
Post * (ESG Messages)	0.109***	0.017
	(0.039)	(0.083)
Post * (E Messages)	0.040	0.058
	(0.037)	(0.086)
Post * (S Messages)	0.034	-0.064
	(0.034)	(0.089)
Post * (G Messages)	0.124***	-0.125
	(0.041)	(0.085)
Control Mean	0.080	-2.060
Observations	1,327,167	238,401
R-squared	0.555	0.875
Firm FE	Yes	Yes
Industry-Day FE	Yes	Yes
Firm Clusters	Yes	Yes

Notes: This table presents heterogeneous treatment effect estimates across experimental arms on investor responses based on Equation (7). The dependent variables are the cumulative ratio of ESG-related questions and general question sentiment scores, respectively. The independent variable is an interaction term between post-treatment indicators and treatment arm dummies, capturing group-specific average treatment effects. Both regressions include firm fixed effects and industry-by-day fixed effects. Standard errors in parentheses are clustered at the firm level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table A13. Aggregate and Heterogeneous Effects on Cumulative Abnormal Returns

	Fama-French Three-Factor Model						Fama-French Five-Factor Model					
	(1) CAR[0,4]	(2) CAR[0,4]	(3) CAR[0,9]	(4) CAR[0,9]	(5) CAR[0,20]	(6) CAR[0,20]	(7) CAR[0,4]	(8) CAR[0,4]	(9) CAR[0,9]	(10) CAR[0,9]	(11) CAR[0,20]	(12) CAR[0,20]
Treat	0.000		-0.001		-0.002		-0.000		-0.002		-0.002	
	(0.002)		(0.002)		(0.003)		(0.002)		(0.002)		(0.003)	
ESG Messages		-0.000		-0.003		-0.003		-0.001		-0.004		-0.003
		(0.002)		(0.003)		(0.004)		(0.002)		(0.003)		(0.004)
E Messages		0.001		0.002		0.001		0.001		0.002		0.001
		(0.002)		(0.003)		(0.004)		(0.002)		(0.003)		(0.004)
S Messages		0.000		-0.001		-0.004		-0.000		-0.002		-0.003
		(0.002)		(0.003)		(0.004)		(0.002)		(0.003)		(0.004)
G Messages		-0.001		-0.002		-0.004		-0.001		-0.003		-0.002
		(0.002)		(0.003)		(0.004)		(0.002)		(0.003)		(0.004)
Control Mean	0.003	0.003	-0.001	-0.001	-0.006	-0.006	0.002	0.002	-0.000	-0.000	-0.013	-0.013
Observations	4,846	4,846	4,846	4,846	4,846	4,846	4,846	4,846	4,846	4,846	4,846	4,846
R-Squared	0.099	0.099	0.109	0.110	0.074	0.074	0.050	0.051	0.090	0.091	0.102	0.102
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: This table presents aggregate and heterogeneous treatment effect estimates of cumulative abnormal returns (CAR) using methodology outlined in Appendix E. The first six columns use the Fama-French three-factor model to calculate expected returns, while the last six columns use the Fama-French five-factor model. We present CAR estimates using different event windows: [0,4] refers to one week (5 trading days) after the start of our experiment, [0,9] refers to two weeks (10 trading days), and [0,20] refers to one month (21 trading days). Odd-numbered columns report average treatment effects using treat dummies. Even-numbered columns report group-specific average treatment effects using treatment arm dummies. Given the cross-sectional data structure, all regressions include industry fixed effects with robust standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table A14. Heterogeneity of Firms' Online Responses Across Productivity Measures

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	Length	Sentiment	ESG Words	Length	Sentiment	ESG Words	Length	Sentiment	ESG Words	Length	Sentiment	ESG Words
<25% Percentile	6.203*	0.141	5.119***	6.423*	0.126	5.155***	10.638***	1.452	5.711***	3.089	-1.013	5.031***
	(3.438)	(1.057)	(0.149)	(3.402)	(1.045)	(0.148)	(3.572)	(1.087)	(0.154)	(3.199)	(0.997)	(0.149)
25-50% Percentile	17.845***	4.087***	5.791***	16.070***	3.221**	5.818***	8.942**	1.791	5.470***	12.516***	1.849	5.551***
	(3.984)	(1.271)	(0.160)	(4.145)	(1.296)	(0.160)	(3.787)	(1.202)	(0.163)	(3.870)	(1.202)	(0.157)
50-75% Percentile	18.237***	4.570***	5.850***	14.376***	3.676***	5.786***	18.048***	4.704***	5.718***	17.045***	4.410***	5.824***
	(3.886)	(1.267)	(0.159)	(3.720)	(1.237)	(0.153)	(3.859)	(1.236)	(0.159)	(3.880)	(1.246)	(0.164)
>75% Percentile	21.329***	6.280***	5.918***	27.158***	8.176***	5.963***	26.180***	6.975***	5.755***	33.034***	10.100***	6.276***
	(3.896)	(1.254)	(0.160)	(3.957)	(1.278)	(0.168)	(4.194)	(1.383)	(0.166)	(4.289)	(1.400)	(0.167)
Measure	ROA	ROA	ROA	ROE	ROE	ROE	TFP 1	TFP 1	TFP 1	TFP 2	TFP 2	TFP 2
Control Mean	75.971	23.617	0.193	75.971	23.625	0.193	75.643	23.544	0.193	75.709	23.552	0.191
Observations	144,872	144,872	144,872	144,267	144,267	144,267	142,399	142,399	142,399	139,788	139,788	139,788
R-Squared	0.310	0.302	0.558	0.310	0.302	0.559	0.309	0.301	0.556	0.309	0.301	0.559
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry-Day FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: This table reports heterogeneous treatment effects across productivity quartiles for firms' responses on Q&A platforms, estimated using Equation (6). The dependent variables include answer length (the number of Chinese characters), the number of ESG keywords in answers, and sentiment scores from textual analysis. The independent variables are interaction terms between an indicator for whether a specific question belongs to our treatment and productivity quartile dummies (for ROA, ROE, and two TFP measures, respectively). All regressions control for question length and sentiment and include firm and industry-by-day fixed effects. Standard errors in parentheses are clustered at the firm level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table A15. Heterogeneity of Firms' Offline Actions Across Productivity Measures

	ESG Ratings				ESG Report	Communications	Negative Media Reports	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Syntao	Wind	QuantData	Hithink	Release Dummy	Mention ESG	Regulation Violations	Supply Chain Issues
Post * Treat	0.604	0.067	0.121	0.103	1.756*	1.245	-0.080	-0.023
	(0.619)	(0.164)	(0.347)	(0.097)	(1.018)	(0.809)	(0.138)	(0.045)
Post * Treat * ROA	11.979**	3.994***	12.848***	1.572*	36.706***	14.733	-3.168***	-0.744***
	(5.569)	(1.119)	(2.329)	(0.814)	(6.235)	(9.509)	(0.892)	(0.166)
Observations	32,946	33,038	32,751	33,170	33,894	11,458	1,324,596	1,324,596
R-Squared	0.815	0.815	0.863	0.920	0.755	0.660	0.025	0.021
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	No	No	No	No	Yes	No	No	No
Quarter FE	Yes	Yes	Yes	Yes	No	No	No	No
Industry-Day FE	No	No	No	No	No	Yes	Yes	Yes

Notes: This table reports regression estimates of offline actions across productivity measures based on Equation (9). The dependent variables include firms' ESG ratings from cited and uncited agencies, the release of ESG reports, mentions of ESG during institutional investor communications, and negative ESG-related media reports. All dependent variables are scaled by 100 to improve coefficient readability. The independent variables include the interaction term between post and treat dummies to measure the average treatment effect, along with an interaction term with ROA to capture heterogeneity. Based on the data structure, columns 1-4 include firm and quarter fixed effects, column 5 includes firm and year fixed effects, and columns 6-8 include firm and industry-by-day fixed effects. Standard errors in parentheses are clustered at the firm level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table A16. Heterogeneity of Firms' Online Responses Across Transparency Measures

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	Length	Sentiment	ESG Words	Length	Sentiment	ESG Words	Length	Sentiment	ESG Words	Length	Sentiment	ESG Words
<25% Percentile	33.144***	9.179***	6.108***	25.670***	7.055***	5.755***	26.973***	7.275***	5.898***	31.554***	8.706***	6.011***
	(3.773)	(1.241)	(0.158)	(3.737)	(1.228)	(0.160)	(3.963)	(1.291)	(0.157)	(3.765)	(1.192)	(0.165)
25-50% Percentile	19.872***	5.278***	5.892***	19.493***	5.281***	5.884***	17.950***	4.157***	5.881***	18.186***	4.719***	5.862***
	(3.875)	(1.238)	(0.158)	(3.752)	(1.218)	(0.150)	(3.787)	(1.226)	(0.161)	(3.932)	(1.290)	(0.155)
50-75% Percentile	3.512	0.253	5.308***	9.872***	1.738	5.479***	8.141**	1.530	5.498***	5.639	0.239	5.543***
	(3.750)	(1.202)	(0.155)	(3.746)	(1.160)	(0.154)	(3.536)	(1.071)	(0.163)	(3.817)	(1.213)	(0.151)
>75% Percentile	3.572	-0.744	5.292***	7.148*	0.568	5.560***	9.982**	1.953	5.465***	6.996*	1.041	5.245***
	(3.691)	(1.120)	(0.157)	(4.116)	(1.299)	(0.167)	(3.910)	(1.265)	(0.153)	(3.659)	(1.145)	(0.157)
Index	Summary	Summary	Summary	Internal	Internal	Internal	External	External	External	Market	Market	Market
Control Mean	75.931	23.604	0.193	75.951	23.618	0.193	75.975	23.623	0.193	75.898	23.601	0.192
Observations	144,872	144,872	144,872	144,872	144,872	144,872	144,115	144,115	144,115	144,757	144,757	144,757
R-Squared	0.311	0.303	0.559	0.310	0.302	0.557	0.310	0.301	0.559	0.311	0.302	0.558
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry-Day FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: This table reports heterogeneous treatment effects across transparency quartiles for firms' responses on Q&A platforms, estimated using Equation (6). The dependent variables include answer length (the number of Chinese characters), the number of ESG keywords in answers, and sentiment scores from textual analysis. The independent variables are interactions between an indicator for whether a specific question belongs to our treatment and transparency index quartile dummies (for summary index, internal management index, external relationship index, and market research index, respectively). All regressions control for question length and sentiment and include firm and industry-by-day fixed effects. Standard errors in parentheses are clustered at the firm level. *** $p < 0.01$, **$p < 0.05$, *$p < 0.1$.

Table A17. Heterogeneity of Firms' Offline Actions Across Transparency Measures

	ESG Ratings				ESG Report	Communications	Negative Media Reports	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Syntao	Wind	QuantData	Hithink	Release Dummy	Mention ESG	Regulation Violations	Supply Chain Issues
Post * Treat	0.747	0.174	0.491	0.132	2.664***	1.993***	-0.164	-0.043
	(0.590)	(0.159)	(0.343)	(0.095)	(1.014)	(0.754)	(0.135)	(0.045)
Post * Treat * Transparency	-4.828***	-2.092***	0.744	-0.797***	-7.643***	-0.952	0.469**	0.056
	(1.180)	(0.248)	(0.487)	(0.138)	(1.410)	(1.286)	(0.223)	(0.056)
Observations	32,946	33,038	32,751	33,170	33,894	11,458	1,324,596	1,324,596
R-Squared	0.815	0.816	0.863	0.921	0.755	0.660	0.025	0.021
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	No	No	No	No	Yes	No	No	No
Quarter FE	Yes	Yes	Yes	Yes	No	No	No	No
Industry-Day FE	No	No	No	No	No	Yes	Yes	Yes

Notes: This table reports regression estimates of offline actions across transparency measures based on Equation (9). The dependent variables include firms' ESG ratings from cited and uncited agencies, the release of ESG reports, mentions of ESG during institutional investor communications, and negative ESG-related media reports. All dependent variables are scaled by 100 to improve coefficient readability. The independent variables include the interaction term between post and treat dummies to measure the average treatment effect, along with an interaction term with the transparency index to capture heterogeneity. Based on the data structure, columns 1-4 include firm and quarter fixed effects, column 5 includes firm and year fixed effects, and columns 6-8 include firm and industry-by-day fixed effects. Standard errors in parentheses are clustered at the firm level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table A18. Heterogeneity of Firms' Response Across Investor Preferences

	(1) Length	(2) ESG Words	(3) Sentiment
No Neg Comments	14.340***	5.777***	3.500***
	(3.798)	(0.146)	(1.233)
Neg Comments	9.453**	5.359***	2.347
	(4.544)	(0.193)	(1.543)
Control Mean	75.938	0.193	23.613
Observations	144,872	144,872	144,872
R-Squared	0.309	0.557	0.301
Firm FE	Yes	Yes	Yes
Industry-Day FE	Yes	Yes	Yes

Notes: This table reports heterogeneous treatment effects across investor preferences for firms' responses on Q&A platforms, estimated using Equation (6). The dependent variables include firms' response length (measured by the number of Chinese characters), the number of ESG keywords in answers, and the response sentiment. The independent variables include the interaction term between post, treat, and negative comment indicators. The negative comment indicator equals one if a firm belongs to the C1B group and has received negative comments from other investors, zero if a firm belongs to the C1B group but has not received negative comments from other investors, and 99 otherwise. We only present estimates for interactions with the first two cases in this table. All regressions include firm and industry-by-day fixed effects. Standard errors in parentheses are clustered at the firm level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table A19. Market Returns Across Heterogeneity Dimensions

	Log(Tradable A-Share Market Value)		
	(1)	(2)	(3)
Post * Treat	-0.004	0.002	0.003
	(0.008)	(0.008)	(0.008)
Post * Treat * ROA	0.222**		
	(0.099)		
Post * Treat * Transparency		-0.016*	
		(0.010)	
Post * Treat * (No Neg Comments)			0.005
			(0.010)
Post * Treat * (Neg Comments)			-0.023*
			(0.013)
Observations	1,164,510	1,164,510	1,164,510
R-Squared	0.973	0.973	0.973
Firm FE	Yes	Yes	Yes
Industry-Day FE	Yes	Yes	Yes

Notes: This table reports regression estimates of market responses across groups based on Equation (7) and (9). The dependent variable is the log of tradable A-share market value. The independent variables include the interaction term between post and treat dummies to measure the average treatment effect, along with an interaction term with ROA (for column 1), transparency index (for column 2), or negative comments indicator (for column 3) to capture heterogeneity. The negative comment indicator equals one if a firm belongs to the C1B group and has received negative comments from other investors, zero if a firm belongs to the C1B group but has not received negative comments from other investors, and 99 otherwise. We only present estimates for interactions with the first two cases in the last column. All the regressions include firm and industry-by-day fixed effects. Standard errors in parentheses are clustered at the firm level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table A20. Market Returns to ESG Responses and Actions

	Log(Tradable A-Share Market Value)							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Post * Treat * (Z-Score of Reply Length)	0.009*	0.009*	0.008*	0.007	0.008*	0.011	0.010**	0.010**
	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.007)	(0.005)	(0.005)
Post * Treat * (ESG Improvement)	0.030	0.141	0.145***	0.768***	0.044***	0.017	-0.271*	-0.749*
	(0.035)	(0.094)	(0.041)	(0.149)	(0.014)	(0.056)	(0.165)	(0.437)
ESG Improvement Dimension	ESG Ratings: Syntao	ESG Ratings: Wind	ESG Ratings: QuantData	ESG Ratings: Hithink	ESG Report: Release Dummy	Communications: Mention ESG	Media: Regulation Violations	Media: Supply Chain Issues
Observations	632,653	618,774	618,052	617,570	636,361	207,895	636,361	636,361
R-Squared	0.975	0.975	0.975	0.975	0.974	0.970	0.974	0.974
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry-Day FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: This table reports regression estimates of market responses to firms' online reply quality and offline outcome improvements based on Equation (9). The dependent variable is the natural logarithm of daily tradable A-share market capitalization at the firm level. The independent variables include (1) the interaction term between post and treat dummies to measure the average treatment effect, (2) the interaction term z-scored reply length to measure the marginal returns to above-average online response quality, and (3) an interaction term with outcome improvement indicators to measure the marginal returns to offline improvements, with each column using a different improvement measure. All regressions include firm fixed effects and industry-by-day fixed effects. Standard errors in parentheses are clustered at the firm level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table A21. Heterogeneity of Firms' Online Responses Across Leader Traits

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	Length	Sentiment	ESG Words	Length	Sentiment	ESG Words	Length	Sentiment	ESG Words	Length	Sentiment	ESG Words
<25% Percentile	8.172**	1.185	5.094***	10.309***	2.420**	5.169***	14.203***	3.385***	5.340***	14.154***	3.625***	5.308***
	(3.792)	(1.203)	(0.151)	(3.300)	(1.092)	(0.142)	(3.247)	(1.047)	(0.151)	(3.314)	(1.040)	(0.145)
25-50% Percentile	16.495***	3.918***	5.803***	20.274***	4.671***	5.549***	22.361***	5.027***	5.741***	23.621***	5.693***	5.853***
	(4.391)	(1.374)	(0.178)	(3.758)	(1.174)	(0.150)	(4.380)	(1.369)	(0.168)	(4.198)	(1.342)	(0.169)
50-75% Percentile	20.986***	5.712***	5.771***	15.636***	3.924***	5.902***	18.478***	4.096***	5.846***	11.589***	2.634**	5.818***
	(4.049)	(1.298)	(0.175)	(4.034)	(1.324)	(0.161)	(3.857)	(1.267)	(0.157)	(3.976)	(1.272)	(0.154)
>75% Percentile	15.612***	4.045***	6.140***	20.337***	5.046***	6.055***	11.052***	3.317***	5.754***	17.534***	4.011***	5.700***
	(4.403)	(1.427)	(0.185)	(4.252)	(1.327)	(0.181)	(3.680)	(1.163)	(0.158)	(3.704)	(1.195)	(0.165)
Measure	Education	Education	Education	Academia	Academia	Academia	Female	Female	Female	Connection	Connection	Connection
Control Mean	76.234	23.719	0.189	76.167	23.686	0.191	76.008	23.643	0.193	76.009	23.639	0.193
Observations	125,832	125,832	125,832	138,845	138,845	138,845	141,482	141,482	141,482	141,406	141,406	141,406
R-Squared	0.311	0.304	0.553	0.312	0.303	0.560	0.311	0.303	0.557	0.311	0.303	0.557
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry-Day FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: This table reports heterogeneous treatment effects across leader trait quartiles for firms' responses on Q&A platforms, estimated using Equation (6). The dependent variables include answer length (the number of Chinese characters), the number of ESG keywords in answers, and sentiment scores from textual analysis. The independent variables are interaction terms between an indicator for whether a specific question belongs to our treatment and leader trait quartile dummies (for average education, academia co-appointment, percentage of female leaders, and government connections, respectively). All regressions control for question length and sentiment and include firm and industry-by-day fixed effects. Standard errors in parentheses are clustered at the firm level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table A22. Heterogeneity of Firms' Online Responses Across Cultural Factors

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	Length	Sentiment	ESG Words	Length	Sentiment	ESG Words	Length	Sentiment	ESG Words	Length	Sentiment	ESG Words
<25% Percentile	34.525***	7.646***	5.993***	41.017***	9.132***	6.079***	28.573***	6.200**	6.234***	22.716***	4.242	5.558***
	(7.876)	(2.638)	(0.369)	(8.628)	(2.799)	(0.305)	(8.628)	(2.832)	(0.410)	(7.911)	(2.659)	(0.313)
25-50% Percentile	25.143***	5.073**	5.512***	15.397*	3.414	5.348***	14.734**	2.739	5.253***	21.275***	4.528*	5.723***
	(8.493)	(2.521)	(0.361)	(7.986)	(2.599)	(0.390)	(6.890)	(2.133)	(0.282)	(8.143)	(2.741)	(0.389)
50-75% Percentile	37.446***	10.583***	6.542***	25.903***	6.211**	5.766***	40.618***	10.872***	5.940***	37.116***	9.869***	6.310***
	(8.900)	(2.944)	(0.387)	(8.926)	(3.014)	(0.362)	(9.463)	(3.071)	(0.360)	(9.382)	(3.085)	(0.367)
>75% Percentile	6.427	0.336	4.979***	24.293***	5.293**	5.780***	17.368**	3.175	5.586***	24.345***	4.964**	5.424***
	(7.925)	(2.753)	(0.309)	(7.115)	(2.301)	(0.347)	(8.379)	(2.876)	(0.376)	(7.584)	(2.294)	(0.340)
Measure	Jinshi	Jinshi	Jinshi	Confucius	Confucius	Confucius	Zhuxi	Zhuxi	Zhuxi	Genealogy	Genealogy	Genealogy
Control Mean	76.839	23.967	0.194	76.830	23.965	0.197	76.860	23.963	0.196	77.451	0.195	0.195
Observations	32,136	32,136	32,136	32,134	32,134	32,134	32,136	32,136	32,136	31,887	31,887	31,887
R-Squared	0.372	0.364	0.546	0.371	0.364	0.542	0.370	0.363	0.542	0.376	0.365	0.548
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry-Day FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: This table reports heterogeneous treatment effects across cultural factor quartiles for firms' responses on Q&A platforms, estimated using Equation (6). The dependent variables include answer length (the number of Chinese characters), the number of ESG keywords in answers, and sentiment scores from textual analysis. The independent variables are interaction terms between an indicator for whether a specific question belongs to our treatment and cultural factor quartile dummies (for Jinshi density, Confucian Clan density, distance to Zhu Xi Academy, and number of genealogy books, respectively). All regressions control for question length and sentiment and include firm and industry-by-day fixed effects. Standard errors in parentheses are clustered at the firm level. *** $p < 0.01$, **$p < 0.05$, *$p < 0.1$.

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