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

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We conduct a nationwide field experiment on over 4,800 Chinese listed firms to study how investor ESG demand shapes corporate behavior and valuations. We randomly raise ESG concerns on public investor platforms, which generate transparent firm-level ESG demand shocks. Treated firms increase ESG disclosure and actions, and stock market reactions are sharply dimension-specific: environmental inquiries boost valuations, whereas governance concerns trigger persistent skepticism. Productive, opaque firms respond most strongly, consistent with a Spence(1973)-style signaling model in which costly ESG actions credibly reveal quality. Firms also cut advertising and dividends to finance ESG, indicating profit-oriented rather than values-driven 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 (Egorov & Harstad, 2017; Harrison & Scorse, 2010). From 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 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 different 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? What are the market implications for firms pursuing aggressive ESG performance? Why do some firms pursue ambitious pro-social initiatives while others exert only minimal effort or resist altogether? 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 have 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 require firms to provide timely

responses, making our intervention a salient and material event for the management team. Prior work has documented that such platform interactions can significantly influence stock prices, trading volume, and liquidity (Lee & Zhong, 2022; Wong et al., 2024a). 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.

Our analysis yields three main findings that correspond directly to the three research questions. First, we show that firms are highly responsive to decentralized ESG demand: treated firms actively address our concerns by disclosing detailed ESG information and outlining future strategies. These firms subsequently are more likely to reference ESG under other topics, release ESG reports, highlight ESG themes when communicating with institutional investors, disclose environmental metrics, and reduce carbon emissions and pollution violations after our experiment. Second, we find that the market's valuation of these actions depends on the nature of the demand: while environmental initiatives elicit favorable stock market reactions, governance-related inquiries often trigger negative returns, suggesting that investors may perceive the latter as a signal of underlying agency costs. Notably, although our initial intervention is modest, the resulting changes in firm behavior aggregate into redirected capital flows and stock valuation movements. Third, we document a stark selection pattern in take-up: the propensity to adopt ESG initiatives is not uniform, but is concentrated among firms that are *ex-ante* more productive, less transparent, and exposed to ESG-conscious shareholders. These findings are generally robust across various validity checks, including potential spillovers, response biases, alternative specifications, and adjustments for multiple hypothesis testing.

To understand the underlying motives for heterogeneous ESG actions, we develop a simple conceptual model based on the classical Spence (1973) signaling framework. In the model, ESG policies serve as a costly but informative signal that allows high-quality firms to separate themselves when investors face information frictions. This theoretical lens reconciles our empirical results: productive but opaque firms find it optimal to "invest" in ESG as a credible signal of latent quality, thereby capturing valuation gains that less efficient firms cannot afford to pursue. Supporting this interpretation, we further show that treated firms reoptimize their broader signaling portfolio to fund their ESG initiatives: the expenditures on traditional financial and marketing signals, most notably advertising and cash dividends, are reduced after our experiment. Finally, we show that once the signaling channel is accounted for, residual factors such as CEO characteristics or local

norms play a minimal role, suggesting that ESG adoption is fundamentally driven by strategic profit-maximization rather than purely altruistic or cultural motives.

This paper makes four key contributions to the literature. First, we provide the first nationwide 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), unpacking the information diffusion process and establishing 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 managerial ownership (Leland & Pyle, 1977), dividends (Bhattacharya, 1979), advertising (Milgrom & Roberts, 1986), and 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), and, crucially, that

firms adjust their full portfolio of signals when ESG becomes more salient: they substitute away from traditional financial and marketing signals to finance ESG upgrades, rather than simply adding ESG on top of existing "good deeds." 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 collective public appeals to drive meaningful corporate change. In this line of literature, Buntaine et al. (2024) conducted the first large-scale field experiment on Chinese social media and found that public complaints against pollution violations significantly improved firms' environmental compliance. In parallel, several finance and accounting studies adopted similar research designs and conducted field experiments on investor platforms to examine information disclosure (Wong et al., 2024a), emissions (Wong et al., 2024b), and payout policies (Wang et al., 2025). Building on this emerging literature, this study expands the scope of inquiry to broader corporate governance, unpacking the economic mechanisms through which strategic public communication exerts 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. Sections V and VI report the experimental results. Section VII examines the underlying motives behind firms' ESG actions and tests additional hypotheses. Finally, Section VIII concludes.

II. Research Settings

II.1 Investor Online Q&A Platforms

In this study, we leverage two unique investor online Q&A platforms in China. Unlike developed economies, China's stock market is dominated by over 200 million retail investors, who collectively hold 30% of the free-float market value and account for over 60% of the trading volume (Li, 2024; Quan, 2022). To bridge the information gap between these dispersed investors and listed firms, the Shenzhen and Shanghai Stock Exchanges established official Q&A platforms in 2010 and 2013, respectively (see Figure A1). Participation is compulsory: each A-share firm maintains a dedicated community page and acts through a designated senior executive (typically the board secretary) to ensure accountability. When a question is posted, both management and the firm's followers receive alerts, with followers notified again once the firm replies.

As an indispensable channel of first-hand communication, 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. These features position the platforms as a central hub for real-time engagement. Executives now have direct access to investor concerns and can respond promptly through this highly visible communication channel.

Crucially, while these platforms prohibit the disclosure of material new information, they serve as powerful tools for amplifying the salience of existing disclosures and conveying qualitative nuances. The interactive format allows management to offer interpretative context, strategic clarity, and emotional commitment that are often absent from standardized financial reports. This "soft" information is particularly consequential in China's retail-dominated market, where investor attention and sentiment can drive substantial price movements even in the absence of fundamental news (Baker & Wurgler, 2006; Barber & Odean, 2008; Kumar & Lee, 2006; Stambaugh et al., 2012). Consequently, targeted inquiries on these platforms can act as salient attention shocks. By explicitly raising specific issues such as ESG concerns, investors can effectively re-weight market attention toward public but previously neglected attributes, thereby triggering market reactions through salience channels independent of new quantitative disclosures.

In line with this perspective, observational studies confirm that interactions on these platforms are high-stakes events with tangible market consequences. For instance, heightened

investor inquiries are associated with increased trading volume, return volatility, price informativeness, and corporate investment efficiency (Lee & Zhong, 2022; Xu et al., 2024). Furthermore, active investor communication during trading halts has been shown to improve post-halt market liquidity (Lee & Zhong, 2025).

To address the endogeneity concern, a nascent set of experimental studies—Wong et al. (2024a), Wong et al. (2024b), and Wang et al. (2025)—apply randomized interventions on the same platforms, finding that retail investor demands can increase dividends, improve transparency, and reduce emissions. Note that when we started our experiment in 2023, we were not aware of these parallel experiments. Additionally, our study offers four distinct contributions. First, our experiment covers the entire universe of non-financial listed firms in China, providing unmatched generalizability and statistical power, in contrast to other experiments that focus on a subset of firms. Second, we tailor our inquiries with firm-specific data to mimic real investor concerns, allowing for a granular analysis of how productivity, opacity, and investor clientele shape corporate responses. Third, by randomizing emphasis across E, S, and G dimensions, we identify how and why market reactions diverge across ESG facets. Finally, and most crucially, we move beyond short-horizon single outcomes to map the full impact-generating process. Rather than simply observing immediate compliance, we trace how an initial demand shock triggers a cascade of interactions among multiple agents, from online engagement and investor reactions to offline corporate actions and longer-run market valuation. As the first large-scale ESG social experiment, we systematically document the demand-supply dynamics of this growing issue and reveal how small-scale interventions can aggregate into medium-to-long-term equilibrium effects.

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

III.1 Overview

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 firms 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 29 industry leaders that rank first across ESG major rating agencies within their respective industries. 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 industry comparisons and recent ESG-related news in all messages. Sample questions can be found in Appendix A.

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). Since these platforms do not permit comments or threaded discussions, our interactions with each firm concluded immediately after their response. 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.[2] We complement these Q&A interactions with sentiment analysis of forum and social media discussions under our forwarded messages. Beyond online behavior, we track offline responses such as ESG reports and disclosures, 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

[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). Importantly, firms with relatively strong overall ESG performance are free to contest the cited ratings, and we indeed observe such responses in practice, including references to more favorable ESG assessments, ESG-related awards, and explicit discussion of methodological discrepancies across rating systems.

[2] To mitigate potential cross-firm spillovers, we implement a staggered posting schedule and restrict the visibility of ESG questions on platform landing pages. Our intervention accounts for less than 5% of total platform activity and is primarily observable on firm-specific pages, limiting scope for market-wide spillovers. We further test for spillovers from treated to control firms by exploiting random variation in industry-level treatment intensity and find no evidence of differential responses across industries. Finally, Appendix B provides direct evidence against spillovers across treated firms: firms' responses exhibit minimal textual similarity across companies, suggesting that treatment effects are not driven by cross-firm imitation or information diffusion (Table A2 and Figure A6).

participants, (3) broader market adjustments, and (4) equilibrium effects on stock valuations. Together, they provide a complete picture of the demand-supply dynamics in the ESG market.

III.2 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 managed the C1B crosscut arm, forwarding 40% of messages to investor forums and social media within a week of the original post. 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). Each treated firm received approximately two inquiries over the experimental period to ensure a salient yet realistic level of engagement without overburdening the platforms. We initially spread the questions evenly across weekdays, but the actual posting days varied due to censorship delays by platform administrators. Additionally, we halved the posting frequency two weeks after initiation to accommodate extended censorship delays.[3] These contingencies are unlikely to bias our causal estimates, as censorship primarily targets duplication and is independent of firm characteristics. For the crosscut arm C1B, we forwarded 2,359 questions concerning 1,180 firms to Guba, Xueqiu, and Weibo (see Panel B), with forwarding delays randomized between one and seven days regardless of firm response status. Although the active intervention spanned 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.

[3] While this created random variation in the exact timing of treatment delivery, most first-round questions were sent within the first month. We therefore employ a standard difference-in-differences framework rather than a staggered adoption design for our six-month post-treatment analysis.

III.3 Ethical Considerations

Prior to designing this experiment, we have carefully considered its ethical implications. First, both the Shenzhen and Shanghai Stock Exchanges 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).[4]

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 G for methodological details). For transparency, we draw on 16 established measures such as equity structure, supply chain concentration, and board independence (see Appendix H). 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).

[4] This study was registered in the AEA RCT Registry following the completion of data collection. Given the high accessibility and low entry cost of the Q&A platforms, pre-registration could have created a substantial risk of concurrent interventions by third parties and potentially contaminated the experimental environment. For this reason, we did not publicly disclose the research design prior to data collection. It turns out that there were indeed other field experiments conducted through the platform during or after our study, albeit at a much smaller scale and focusing on unrelated topics. We note, however, that the study protocols were formalized and submitted for IRB approval at the University of Hong Kong immediately after the pilot phase (ID: EA240235).

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 C 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 opinions.

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 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 several dimensions of firms' ESG offline actions: release and quality of ESG reports, ESG discussions with institutional investors, environmental information disclosure, carbon and air pollutant emissions, ESG-related news coverage, and supplemental annual records such as litigation and green patents. For ESG reports, we scrape firm websites regularly to obtain all historical reports in PDF format and use OCR techniques to access their contents and construct quality measures. For institutional investor communications (such as during site visits and interviews), 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 D for details). For environmental information disclosure, we obtain data on environmental performance, resource consumption, and emissions from the CSMAR. Given the heterogeneity in firms' disclosure items, we construct three binary indicators capturing whether firms disclose information in each category in a given year. For media coverage, we collaborate with YoujiVest, an ESG data vendor specializing in the Chinese market, to monitor mainstream media outlets and create a daily measure of negative ESG-related news coverage concerning regulation violations and supply chain issues for each listed firm. For daily pollution monitoring, we access data from the Continuous Emission Monitoring Systems (CEMS) at state-controlled key polluting facilities, match facilities to listed firms using subsidiary lists, and calculate violation rates for two major air pollutants (NO_X and SO_2). We successfully matched 1,363 firms during our sample period (slightly more than the 1,134 firms in Wong et al. (2024b)), of which 457

have recorded violations. Additional annual measures from CSMAR, including carbon emission intensity, government procurement, regulation violations, litigation and arbitration cases, and green patents, exhibit substantial missing values due to voluntary reporting and are therefore analyzed as supplementary offline actions in the appendix with firm coverage explicitly noted.

Alternative signaling behaviors: Finally, to examine whether firms strategically reallocate resources toward ESG actions, we collect annual data on six alternative signaling mechanisms from CSMAR: advertising expenditures, cash dividends, charitable donations, poverty alleviation expenditures, managerial shareholdings (in shares), and managerial ownership (in percentage). Advertising expenditures and charitable donations are constructed by aggregating itemized entries from financial statements using keyword searches.[5] Given the substantial heterogeneity in reporting standards and magnitudes across firms, we exclude the top and bottom 10% of the distribution and those exhibiting year-to-year changes exceeding fivefold within the same firm. Our results remain robust to alternative definitions and outlier treatments.

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

[5] For advertising expenditures, we sum sales expense items matching keywords such as "advertising," "publicity," "promotion," "planning," "exhibition," and "showroom fees." For charitable donations, we sum non-operating expense items matching keywords such as "external donation," "public welfare donation," and "charitable donation."

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:

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

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-by-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:

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

or

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

where $i, j,$ and t represent firm, industry, and time, respectively. Y_{ijt} and Y_{it} are firms' outcome measures (such as release or quality of ESG reports, question or answer spillovers, question sentiments, and market value, 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-by-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_{ijt} and ε_{it} are error terms. 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-by-day 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:

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

or

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

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:

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

or

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

or

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

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-by-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 helps 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

$$Y_{it} = \sum_{\tau=a,\tau\neq-1}^{b} (\alpha_{\tau 1} \times treat_i \times \mathbb{1}[t = \tau]) + \sum_{\tau=a,\tau\neq-1}^{b} (\alpha_{\tau 2} \times treat_i \times \mathbb{1}[t = \tau] \times K_i) + \mu_i + \varphi_t + \varepsilon_{it} \quad (10)$$

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.

To address potential Type I error concerns arising from our multiple outcome variables, we implement the Benjamini and Hochberg (1995) procedure to control the False Discovery Rate. As detailed in Appendix J, our primary results remain largely robust to these adjustments. While the statistical significance of certain offline actions and market responses is attenuated, the overall qualitative patterns remain consistent with our baseline estimates.

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 reports 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-by-day fixed effects to account for firm-specific and time-varying sectoral shocks (regression results are reported in Table A1).

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.[6]

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 and voluntarily amplify ESG discourse beyond the immediate experimental prompts.[7] Panel A of Figure 4 quantifies this spillover using a dynamic DiD framework, tracking cumulative mentions of ESG keywords in responses to all platform inquiries after our experiment. Treated firms exhibit a sustained increase

[6] Appendix B provides a battery of validation checks, showing no evidence of systematic response replication, AI-generated content, or strategic targeting of our experimental prompts. Furthermore, we find no indication of "ESG-washing" that lacks substantive accountability mechanisms. These checks mitigate key endogeneity concerns, supporting the causal interpretation of our findings.

[7] One potential concern is whether firms perceived the government or regulators, rather than retail investors, as the true audience of our inquiries. Our textual analysis of the 4,992 corporate responses suggests this is unlikely. Only 19 responses (0.38%) explicitly mentioned the "Party" and 40 (0.81%) mentioned the "government." In stark contrast, 3,168 responses (63.79%) explicitly addressed "investors," and 1,454 (29.28%) discussed "operations." These patterns indicate that management teams predominantly viewed these inquiries through the lens of shareholder engagement and corporate strategy rather than political compliance.

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. In Figure A8, we provide examples from the data where treated firms begin to proactively embed ESG content into unrelated investor dialogues, such as pre-earnings announcements.

Complementing this supply-side response, our analysis detects significant spillovers in retail investor demand. The public architecture of the Q&A platforms allows participants to observe and adopt the lines of inquiry introduced by our experiment. Examples in Figure A9 demonstrate this dynamic: investors extend discussions from firms' own ESG ratings to the ESG performance of their partners for treated firms, while other investors begin mimicking our syntax to question ESG risks in financing for control firms. 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 before moderating gradually. The DiD estimate indicates that the share of ESG questions directed at treated firms nearly doubles the control mean (a 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)? To address this question, we examine a broad set of offline firm behaviors organized into three categories. We begin by analyzing corporate ESG disclosure practices, which constitute the most direct and immediate response to investor scrutiny. We then examine concrete operational changes in environmental performance and ESG-related incidents. Finally, we assess whether these behavioral shifts are reflected in third-party ESG ratings, which synthesize information across multiple dimensions and serve as market-recognized quality signals.

ESG Disclosure and Communication. Figure 5 documents firms' disclosure responses along three margins (with estimates reported in columns 1–5 of Table A6). First, we examine the issuance of standalone ESG reports, which represent costly and verifiable commitments requiring substantial organizational resources to compile, audit, and publish. While a general upward trend in ESG disclosure driven by regulatory shifts is evident across all firms, our DiD design effectively

nets out the common macro-level shock and identifies a significantly positive estimate of 2.8% for treated firms, equivalent to 81 additional reports in 2024. This suggests that randomly treated firms are significantly more likely to release an ESG report a few months after the public demand is initiated. Importantly, Table A7 reveals that these new reports exhibit quality comparable to pre-existing disclosures across multiple dimensions: readability metrics, NLP-derived measures of specificity and boilerplate language, and dictionary-based keyword counts. This pattern rejects the hypothesis that firms prioritize low-effort "check-the-box" disclosures solely to appease investors.

Second, we investigate whether firms strategically amplify their ESG visibility during private interactions with institutional investors, who wield considerably greater influence over corporate valuations than retail shareholders. Panel B of Figure 5 presents textual analysis of institutional investor meeting transcripts, documenting a 1.95% increase in ESG mentions for treated firms, which nearly matches the control mean. Table A8 reveals that this rise is predominantly driven by firms proactively introducing ESG topics rather than responding to investor inquiries, suggesting a deliberate reorientation of corporate messaging rather than passive accommodation.

Third, we examine whether firms enhance transparency by publicly disclosing specific environmental metrics in their voluntary reports or filings. Panel C of Figure 5 and columns 3–5 of Table A6 show that treated firms exhibit significantly higher rates of voluntary disclosure for pollution emissions (2.7% increase), waste generation (4.4%), and water consumption (2.7%) relative to control firms. These disclosure decisions are consequential in the sense that they expose firms to heightened scrutiny and potential reputational costs if performance deteriorates, suggesting genuine commitment rather than superficial compliance.

Concrete Operational Changes. We further examine whether our experiment triggered concrete operational changes and measurable environmental and social impacts, such as carbon emission intensity, pollution violations, and negative media coverage. Note that these metrics impose considerably higher data requirements: many outcomes are observable only for firms that voluntarily disclose (e.g., carbon emissions), while others represent rare events with limited statistical power. For instance, pollution violations occur at an average rate of 1.10% in our sample, and media coverage of ESG issues averages just 1.78 regulatory violations and 0.36 supply chain incidents per firm during our observation window. Consequently, null findings for these low-frequency outcomes should be interpreted with appropriate caution given power constraints.

Despite these limitations, we document suggestive evidence of operational improvements along several dimensions, as reported in Appendix Table A9. Columns 1–3 reveal that treated firms exhibit lower carbon emission intensity in the year following treatment, with a 2.4% decline

(significant at the 10% level) driven primarily by reductions in Scope 1 emissions (direct emissions from owned or controlled sources) rather than Scope 2 emissions (from purchased electricity). Similarly, columns 4–5 show modest declines in regulatory violations for traditional air pollutants (NO_X and SO_2), though the latter do not reach conventional significance thresholds given the rarity of such events.[8]

Media coverage provides an independent signal of firms' ESG reputational risk. Columns 6–7 document that treated firms experience a relative reduction in negative media reports related to regulatory violations, with an effect size of 0.25 incidents (significant at the 10% level) against a control mean of 0.71. Other categories of negative ESG coverage, such as supply chain issues, exhibit directionally similar patterns but lack statistical precision due to their extreme rarity.

For ESG dimensions requiring longer-term investments or structural changes, such as securing government procurement contracts, reducing overall regulatory violations, lowering litigation and arbitration incidence, or increasing green patent applications (columns 8–11), we observe no significant treatment effects within our observation window. This null result likely reflects both the extended time horizon required for such outcomes to materialize and the relatively modest magnitude of our experimental shock. Firms may rationally prioritize low-hanging fruit (disclosure and incremental operational adjustments) over costly, long-term strategic reorientations in response to transient demand signals from dispersed retail investors.

Third-Party ESG Ratings. Do these disclosures and operational improvements translate into higher ESG ratings from independent third-party agencies? Figure 6 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.,

[8] The magnitude of our findings (a 1.46% reduction in NO_X and 1.02% in SO_2 violations) is more conservative than the 12.2% reduction reported in Buntaine et al. (2024), primarily reflecting differences in treatment intensity. While Buntaine et al. (2024) directly targeted existing violations by mobilizing citizen complaints to local environmental protection agencies, our study examines investor-led engagement without regulatory enforcement. Our estimates are also smaller than the 4.2% reduction documented in Wong et al. (2024b), for two reasons. First, Wong et al. (2024b) restrict attention to firms with prior violations, while our experiment covers the full universe of non-financial listed firms, including those with high baseline compliance. Second, their three-month observation window likely captures short-term tactical responses, whereas our longer horizon reflects more persistent and systemic adjustments. Taken together, our results provide a broader, market-wide lower bound for the efficacy of ESG-driven online engagement.

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 all four panels, treated firms exhibit positive trajectories in ESG ratings relative to control firms, with effects materializing gradually as agencies process new information and update their assessments.[9] Importantly, these gains are unlikely to reflect collusion between firms and agencies, as the pattern persists even for uncited agencies in Panels C and D. While certain agencies (e.g., Wind and QuantData) factor online ESG discourse into their evaluations, Q&A platform activity receives only marginal weight relative to substantive indicators such as regulatory penalties or legal proceedings. This effectively rules out the possibility that our experimental questions serve as the primary driver of rating changes. The consistency of treatment effects across agencies with heterogeneous methodologies further reinforces our interpretation that firms undertake verifiable ESG improvements detectable through diverse information channels.

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. Given that our randomized treatment assignment is orthogonal to concurrent market fundamentals, we can cleanly isolate the causal effect of RCT-induced adjustments on stock performance free from confounding market trends.

Figure 7 traces the evolution of market value for treated versus control firms. We detect no statistically or economically significant effect at any horizon, with point estimates consistently indistinguishable from zero. These findings indicate that market participants price the opposing forces of scrutiny and response as roughly equivalent, 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

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

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 similar 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 generate 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.

Beyond online engagement, Table A12 examines firms' offline follow-up actions across treatment arms. These outcomes generally rely on smaller samples and low-frequency events, limiting statistical power to detect sharp differences between treatments. Directionally, however, the patterns align with online engagement: firms receiving E prompts tend to exhibit larger and more systematic changes in subsequent behavior, including higher rates of ESG report issuance, more frequent ESG references in communications with institutional investors, and improvements in ESG ratings from uncited agencies. 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 to disentangle dimension-specific effects across the three ESG pillars.

Panel A compares the volume of ESG-related questions directed at treated versus control firms. Mirroring the trend in question spillovers shown in Figure 4, G messages drive the most pronounced investor engagement, with treated firms receiving 1.55 times as many ESG questions as the control mean. While E and S messages also stimulate investor interest, the relative increases are more modest (50% and 42.5%, respectively). These patterns suggest investors may perceive initial G-related disclosures as insufficiently transparent, necessitating follow-up scrutiny to resolve residual informational frictions.

Sentimental analysis of investor inquiries 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 following the release of annual reports in April 2024. This contrasts sharply with the E treatment group, where sentiment stabilizes or even improves following proactive disclosures and tangible actions. S-treated firms show no significant sentiment shifts, aligning with their intermediate investor engagement levels. Taken together, these results suggest that while all ESG shocks increase salience, only E-related interactions mitigate investor concerns. In comparison, G-related inquiries trigger persistent skepticism.

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

How do these heterogeneous supply- and demand-side dynamics aggregate into equilibrium market outcomes? Figure 10 examines market value 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 2.0% increase in market value, translating to an average gain of 260 million RMB ($37 million USD) per firm relative to the December 2023 baseline. In contrast, firms receiving S messages see modest gains, while firms in the G message group face a clear downward trend (although statistically insignificant). Although these magnitudes are modest compared to the high volatility of A-share indices during this period (which fluctuated between 9% and 30%), the direction and scale of these responses are qualitatively consistent with the documented impacts of reputational shocks and shareholder activism (Akey et al., 2023; Flammer, 2015). In Appendix E, we further replicate this analysis using share prices and cumulative log returns as outcomes and find quantitatively larger coefficients and higher statistical significance.

In our setting, these valuation effects emerge gradually rather than immediately after the experiment. This temporal pattern is corroborated by our short-window analysis of Cumulative Abnormal Returns (CAR) presented in Appendix E and Table A14, which shows statistically negligible immediate market reactions.[10] This suggests that the market responds not merely to the initial inquiry but to the cascade of subsequent real-world changes it incentivizes. For example, retail investors may have gradually 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 that firms receiving E, S, or G questions are balanced *ex-ante*, we can attribute these distinct trajectories to the specific content of the ESG intervention rather than concurrent market trends.

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 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

[10] While cumulative abnormal returns (CARs) are standard for capturing immediate reactions, we employ a difference-in-differences (DiD) design for our medium- to long-term analysis to ensure rigorous causal identification. As demonstrated by Goldsmith-Pinkham and Lyu (2025), specification bias accumulates in long-horizon event studies as constant expected return assumptions become untenable, confounding treatment effects with model misspecification. This issue is particularly salient in our setting, where a market-wide intervention correlates with broader market conditions, making it difficult for market models to isolate treatment effects from systemic shifts. Our DiD framework addresses these concerns by accounting for firm and time fixed effects without relying on specific asset pricing models.

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 latent agency problems, while viewing E actions as more credible signals of overall firm quality and management competence.

Collectively, 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 risks or structural 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

Our findings thus far address the first two research questions. In response to divergent public demands for ESG improvements, firms significantly increase their online engagement with ESG topics, improve their ESG ratings and disclosure practices, and enhance substantive environmental performance, such as emissions reduction. These effects manifest heterogeneously across ESG pillars, with environmental initiatives receiving the strongest response. Regarding market implications, we find that investors reward firms pursuing ambitious ESG performance with higher valuations, particularly when these efforts are accompanied by credible signals such as detailed online responses and quantifiable environmental disclosures. The close alignment between firms' online commitments, offline actions, and positive market reactions suggests that ESG improvements serve as value-enhancing activities rather than mere window dressing.

This brings us to our third question: why do firms differ so markedly in their ESG ambitions? To rationalize our findings and guide the heterogeneity analysis, we develop an illustrative signaling model, with formal derivations provided in Appendix F. Building on Spence's (1973) classical framework, the model formalizes our central argument: firms undertake costly ESG actions (especially E actions with positive market reward) 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 valuation 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. Given that productivity is not directly observable, we rely on imperfectly measured proxies to infer the relationship. In Panel A of Figure A12, we use four variables: ROA, ROE, and two TFP measures based on firms' value added and revenue to approximate firms' inherent potential to earn profits (see Appendix G 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.

We next examine whether stronger signals by high-productivity firms are accompanied by tangible real actions. In Table A16, we examine the heterogeneity of their offline ESG actions in terms of publication of ESG reports, mentions of ESG to institutional investors, environmental information disclosure, and ESG ratings. For all measures, higher values indicate better ESG performance, and we find that the interaction term between the DiD estimator and ROA (the proxy for productivity) is significantly positive in most cases. In summary, firms do act on their

ESG commitments. High-productivity firms that send the strongest signals are observed to have greater operational capacity 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 H for details). Similar to productivity measures, the transparency sub-indices exhibit low pairwise correlations (Panel B of Figure A12), 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.[11] 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 A18, we further investigate whether these less transparent firms take more ESG actions than their more transparent counterparts. The results support our hypothesis. Columns 1–2 show that low-transparency firms make greater efforts to release ESG reports and discuss ESG with investors. This pattern extends to environmental disclosures in columns 3–5, where low-transparency firms are significantly more likely to begin reporting emissions, waste generation, and water consumption after treatment. Finally, columns 6–9 demonstrate that these firms achieve larger ESG rating improvements across both cited and uncited agencies. Notably, we document an economically negligible correlation between transparency and productivity (coefficient of -0.044

[11] While we focus on the heterogeneity across these indices in the main text, results separate for different indicators are included in Figure A13.

for ROA and transparency index). As shown in Figure A14, the transparency heterogeneity results remain robust when controlling for productivity in the regressions. This suggests that transparency serves as a distinct driver of firms' ESG actions, operating independently of firm productivity.

VII.3 Investor Preferences and ESG Responses/Actions

Proposition 3 suggests that firms with more ESG-conscious investor bases have stronger 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.

Among the 1,180 firms in the forward crosscut group, 507 (42.97%) received direct responses from retail investors. This response rate reflects both varying levels of investor attention and platform-level constraints, such as posting frequency limits and administrative traffic controls.[12] Some posts were hidden or removed after a few days, which limited the scope of potential interactions. Nonetheless, we collected 1,100 comments, averaging two per firm with a median length of 14 Chinese characters. These comments allow us to construct firm-level sentiment scores as a proxy for the ESG consciousness of the retail investor base.

Since ESG is still a relatively new concept in China, retail investors expressed varied reactions to our ESG inquiries. Among firms exposed to investor feedback, 61.74% received at least one negative comment, suggesting limited ESG consciousness among their investor bases (see Figure A15 for examples). The remainder received only positive or neutral comments, indicating a more receptive or ESG-conscious investor clientele. This variation in investor sentiment allows us to examine how firms tailor their ESG signaling based on the composition of their investor base.

To isolate the effect of investor sentiment conditional on receiving attention, we restrict our analysis to the 1,180 firms that received forwarded Q&A messages. We then examine the

[12] A small subset of forwarded posts (16 firms, or 1.36% of the C1B sample) was subject to community reporting or removal by platform moderators. While the transient nature of deleted posts precludes formal tests for selection bias, we observe no systematic patterns in the firms or messages affected. The forwarded content was highly standardized across treatment arms, and removals appear to be driven primarily by platform-wide algorithmic traffic controls (e.g., posting frequency limits) rather than the specific firm characteristics or message sentiment. To the extent that such censorship restricts our treatment intensity, any resulting bias would likely attenuate our estimates toward zero, suggesting our findings represent a conservative lower bound of the true impact of investor feedback.

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 were exposed to no negative feedback from retail investors tend to provide higher-quality and more positive answers to our ESG inquiries. This finding suggests that firms strategically modulate their signaling behavior based on the perceived payoffs from their stakeholder environment, 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 value 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 A20 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. The results indicate that market responses scale 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 to above-median response quality (proxied by reply length) and (2) marginal returns to ESG improvements across dimensions. Table A21 reveals that both components yield positive and largely significant valuation effects, indicating that investors reward high-quality ESG engagement alongside substantive enhancements. In particular, disclosures of emissions and water consumption elicit positive and significant market responses, consistent with investors' preference for standardized, verifiable ESG metrics. While we do not claim a causal interpretation of these results, the consistency across firms' online responses, offline actions, and market reactions provides compelling evidence that the observed corporate behaviors are strategically aligned with the predictions of our signaling model.

VII.5 Crowding-Out Effect on Alternative Signaling Channels

A central tenet of the signaling framework is that credible signals are costly. If firms are indeed profit-maximizing agents operating under resource constraints, the decision to ramp up ESG signaling in response to our intervention should not occur in isolation. Instead, we expect rational firms to optimize their signaling portfolio by reallocating resources from other, temporarily less salient signaling channels to fund the heightened demand for ESG visibility. To test this substitution effect, we examine whether the treatment crowds out other well-documented signaling behaviors, including advertising expenditures, cash dividends, charitable donations, poverty alleviation expenditures, and managerial equity ownership (Bhattacharya, 1979; Elfenbein et al., 2012; Leland & Pyle, 1977; Milgrom & Roberts, 1986).

Table A22 reports the average treatment effects on these alternative behaviors. Columns 1 and 2 reveal a statistically significant crowding-out effect on the most direct signals. Treated firms reduce advertising expenditures by approximately 6.1% and cash dividends by 5.7% relative to the control group. These magnitudes are economically meaningful and support the view that firms are financially constrained optimizers. Facing an exogenous shock that raises the marginal benefit of ESG signaling (due to increased investor scrutiny and the potential for valuation gains, as shown in Section VII.4), firms strategically divert cash flow from traditional marketing and dividend payouts to finance the ESG improvements.

Columns 3–6 present results for charitable donations, poverty alleviation expenditures, and managerial ownership. While the point estimates are consistently negative, they are not statistically distinguishable from zero. We interpret these null results as the net outcome of two opposing forces. On the one hand, the substitution effect exerts downward pressure on these expenditures as firms conserve cash for high-visibility environmental upgrades. On the other hand, activities such as charitable donations and poverty alleviation are intrinsic components of the "Social" pillar of ESG. Consequently, the direct positive treatment effect on ESG performance likely neutralizes the negative crowding-out effect. For managerial ownership, adjustments are typically subject to institutional frictions and longer planning horizons, making them less responsive in the short run to a demand shock on ESG communication.

Taken together, these findings provide robust empirical support for a rational reallocation channel consistent with our signaling model. Treated firms optimize along a constrained budget, scaling back relatively lower-salience signals to prioritize ESG investments that generate stronger contemporaneous market rewards. This substitution suggests that corporate ESG actions are not

merely additive "good deeds" performed out of slack resources, but are instead strategic components of a firm's broader, rational decision-making process.

VII.6 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 I 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 A16, 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, reduce emissions, 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 accounting for 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, a natural extension is to explore how firms respond to "harder" forms of pressure, such as coordinated shareholder proposals or threats of divestment. Moreover, while we document that firms strategically crowd out traditional financial signals to fund high-visibility ESG metrics, the long-term welfare implications of this reallocation warrant further inquiry. Future work should examine whether this substitution represents an efficient equilibrium adjustment or a distortionary "visibility bias," where firms under-invest in less observable but equally critical productive activities to chase short-term reputational gains. Finally, the origins of the heterogeneous stakeholder demand for ESG remain 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

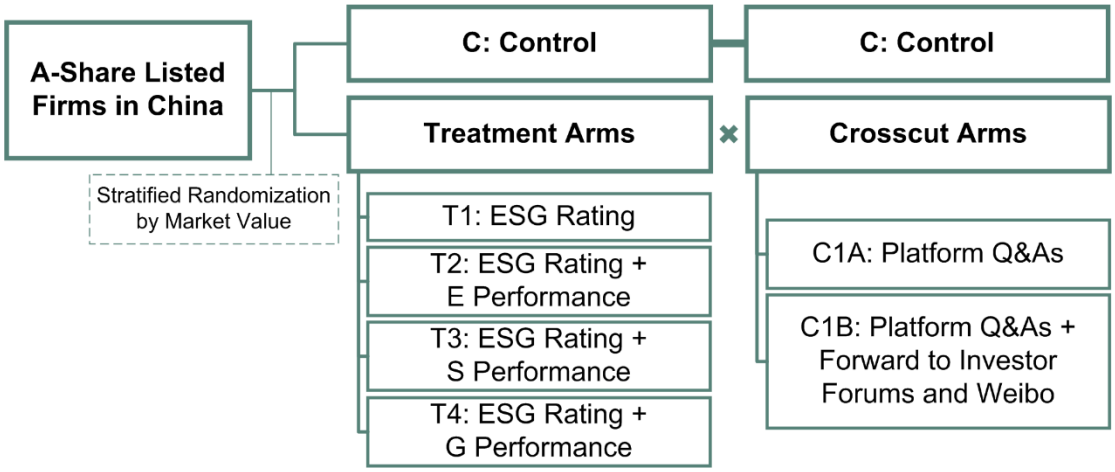


Figure 1. Experimental Design

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).

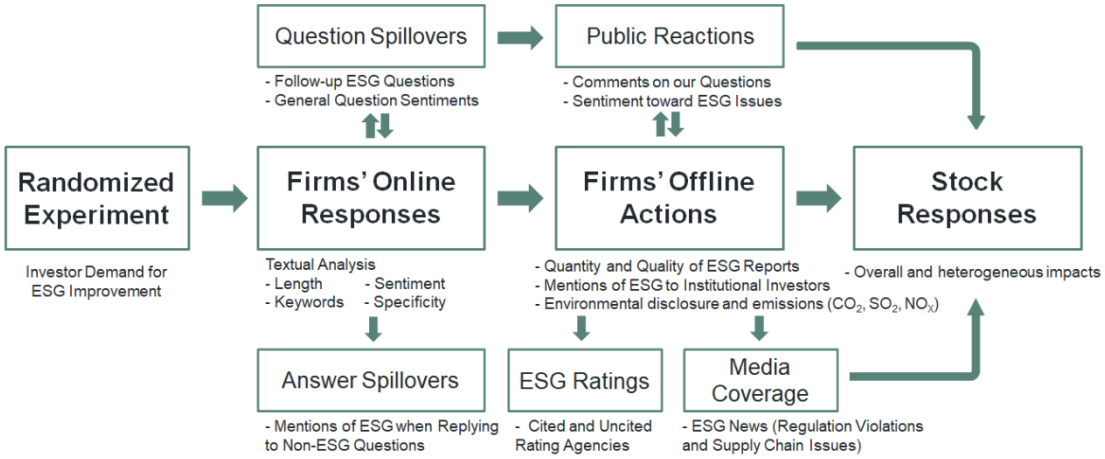


Figure 2. Impact-Generating Process

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.

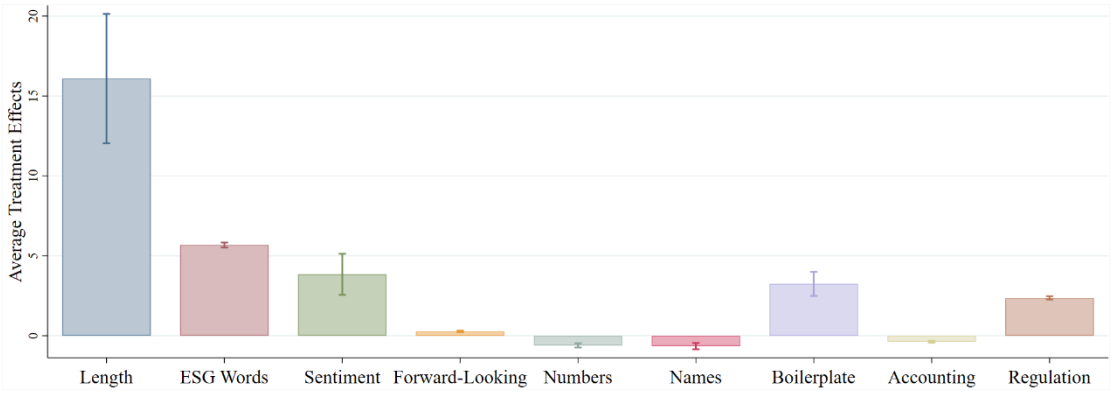


Figure 3. Firms' Aggregate Online Responses

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, 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. 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.

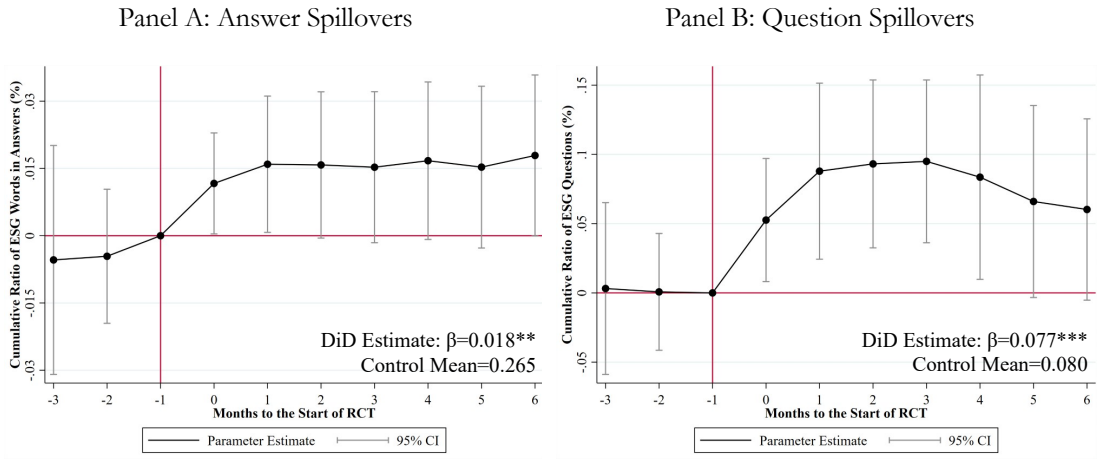


Figure 4. Firms' Answer Spillovers and Investors' Question Spillovers

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 (our experiment excluded) 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.

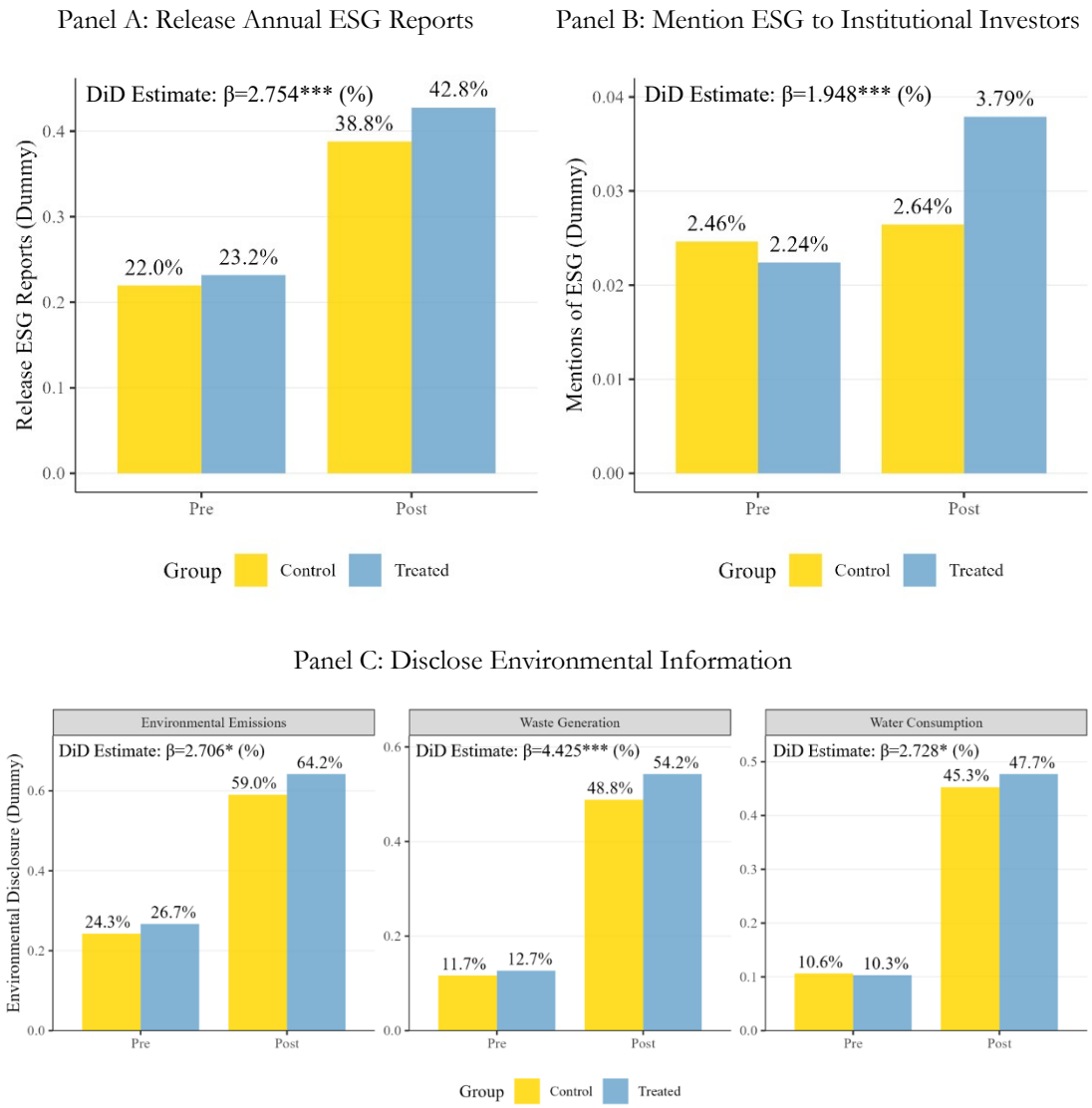


Figure 5. Impacts on ESG Disclosure and Communication Behaviors

Notes: This figure compares ESG disclosure behaviors of treated and control firms before and after the experiment. Panel A presents the proportion of firms releasing ESG reports, Panel B shows the frequency of ESG mentions during institutional investor interactions (site visits, calls, or interviews), and Panel C reports three measures of environmental information disclosure. 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. For environmental disclosures (Panel C), each firm contributes one post-period observation (2024 disclosures in annual social responsibility, environmental, or sustainability reports) and multiple pre-period observations (2016–2023). 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.

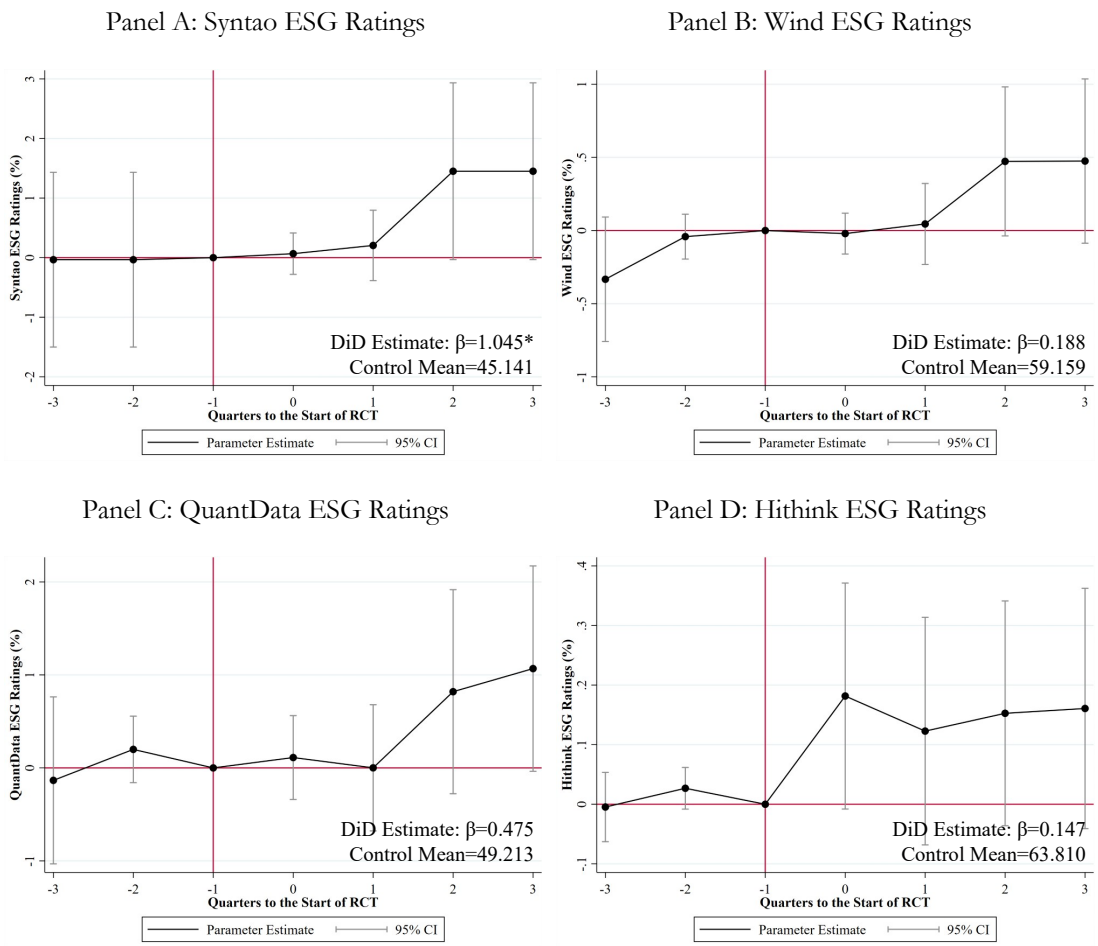


Figure 6. Impacts on ESG Ratings

Notes: This figure presents the estimates of dynamic treatment effects on ESG ratings. 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). 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.

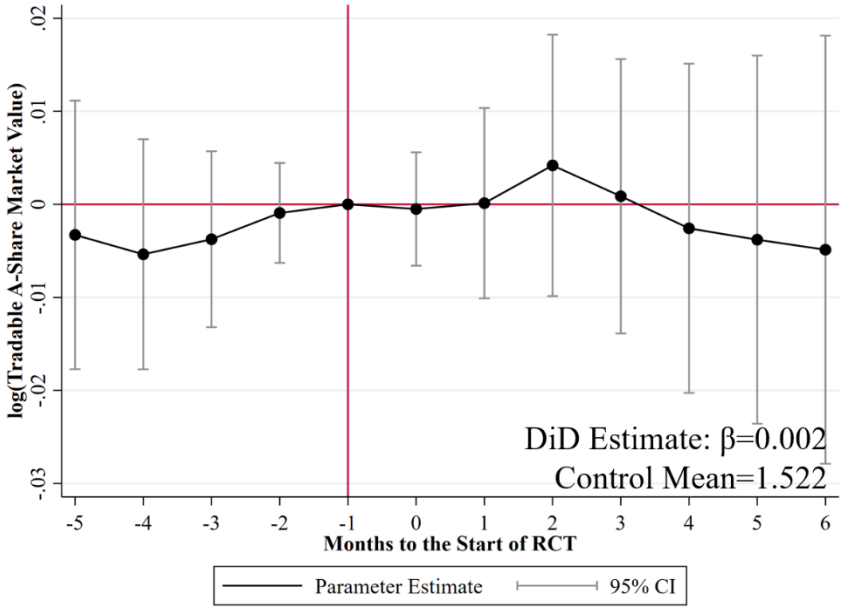
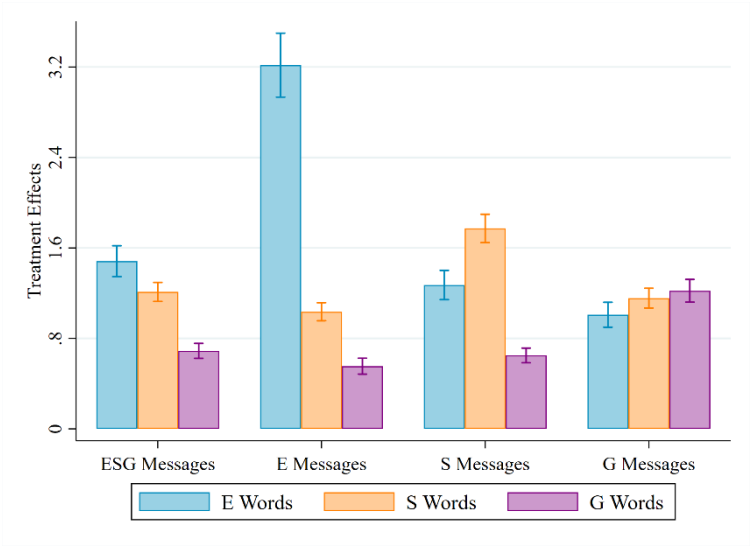


Figure 7. Aggregate Market Responses

Notes: The figure presents the estimates of dynamic treatment effects on firm market valuations, estimated using Equation (4). The dependent variable is the natural logarithm of daily tradable A-share market capitalization 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 A10.

Panel A: ESG Keywords



Panel B: Other Quality Measures

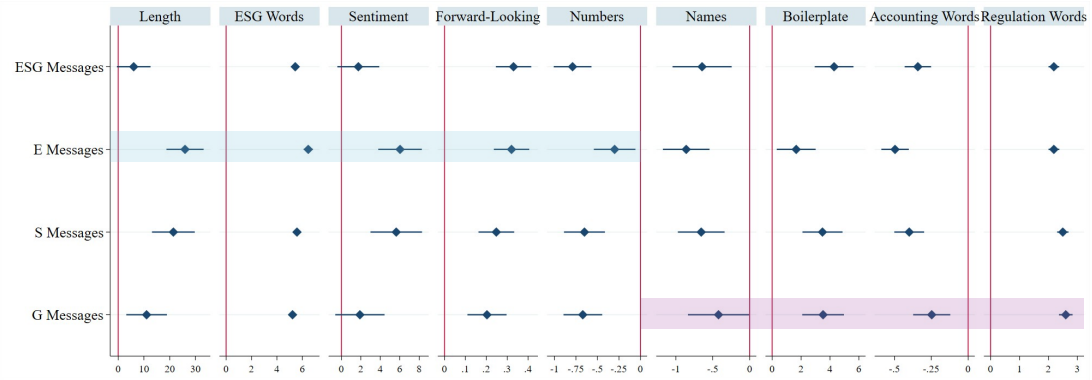
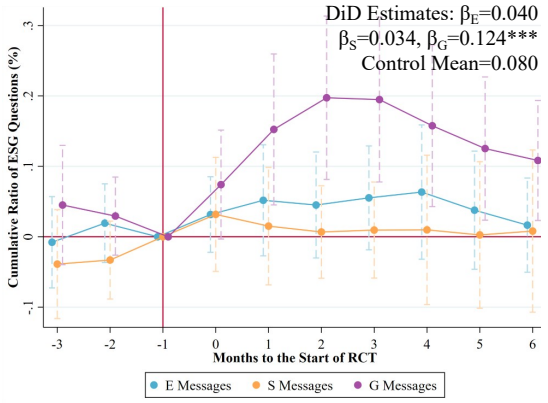


Figure 8. Firms' Responses to E/S/G-Specific Inquiries

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 A11.

Panel A: ESG Question Spillovers



Panel B: General Question Sentiments

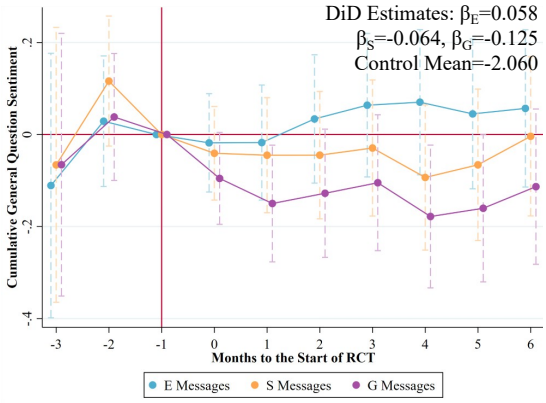


Figure 9. Investors' Responses to E/S/G-Specific Inquiries

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 A13.

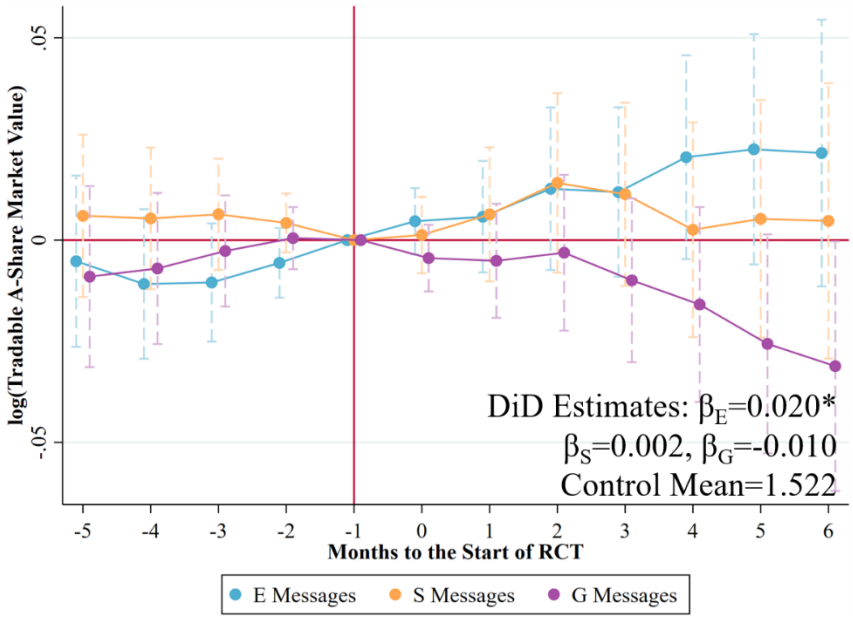
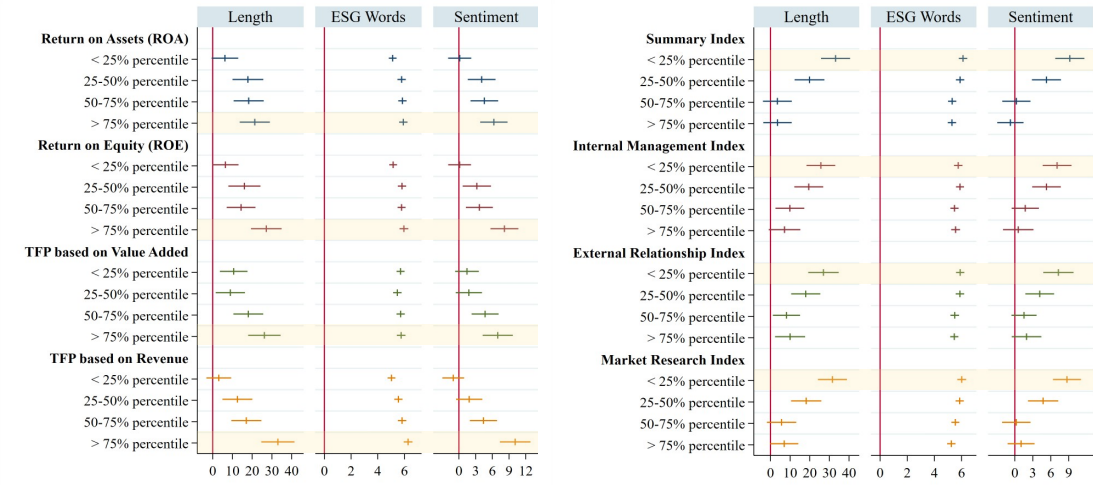


Figure 10. Market Responses to E/S/G-Specific Inquiries

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 market capitalization 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 A10.

Panel A: Heterogeneity Across Productivity Measures

Panel B: Heterogeneity Across Transparency Measures



Panel C: Heterogeneity Across Investor Preferences

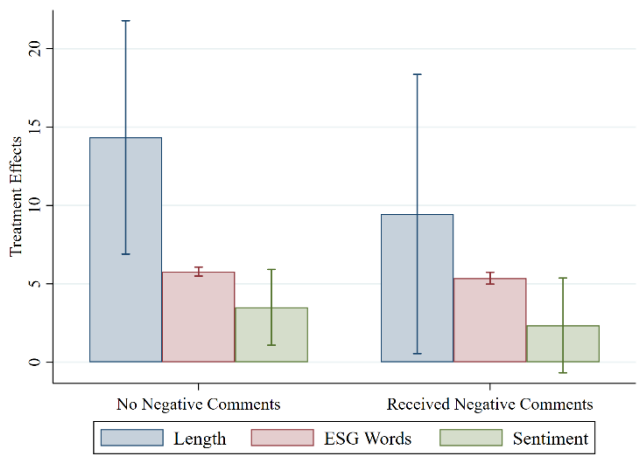


Figure 11. Firms' Responses Vary by Productivity, Transparency, and Investor Preference

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 A15, Table A17, and Table A19.

Panel A: Leader Traits

Panel B: Cultural Factors

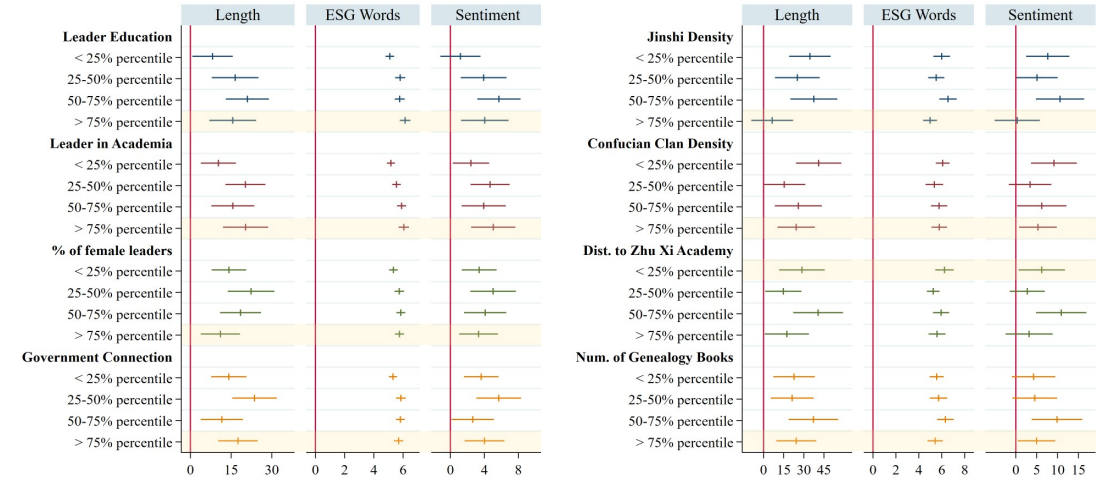


Figure 12. Firms' Responses DO NOT Vary by Leader Trait or Cultural Factor

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 A23 and Table A24.

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 C. 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 C. 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

[T1: ESG Message] 鉴于最近 ESG 话题在投资圈比较热门，我也关注了贵公司的 ESG 表现。发现贵公司在一些权威评级中是 B 附近的水平（例如商道融绿，润灵环球），在机械制造行业中排名还可以改善。我想知道贵公司在提升 ESG 表现方面有哪些考量？是否有制定相应的举措？ESG 报告啥时候考虑发布呢？

[English Translation] Given the recent attention to ESG issues among investors, I have been following your company's ESG performance. I noticed that your company's ratings from several major ESG agencies (such as Syntao and RKS) are around the B level, with room for improvement relative to peers in the machinery manufacturing industry. Could you share the company's considerations regarding improving its ESG performance? Are there any specific initiatives being planned? Additionally, when do you plan to publish an ESG report?

[T1: ESG Message] 车企的可持续发展战略对于未来的业绩增长高度相关，我希望看到更多相关信息比如 ESG 报告，董事会是否能够披露相关信息作为投资参考？现在我只能从三方评级机构万得看到你们的评分是 BB，富时罗素给出的评分是 2.6，和业内领先的公司有差距，会影响投资信心，请问公司是否有相关计划？

[English Translation] An automaker's sustainability strategy is highly relevant to its future performance growth. I would like to see more information in this area, such as an ESG report. Would the board be willing to disclose relevant information for investors' reference? At present, the only information I can find from third-party rating agencies shows a BB rating from Wind and a score of 2.6 from FTSE Russell, which lags behind leading firms in the industry and may affect investor confidence. Does the company have any plans to address this gap?

[T2: E Message] 您好！我关注到贵公司在 ESG 表现上与行业头部企业（如丽珠集团）仍存在相当的差距，你们今年被华测评为 CCC、被路孚特评级为 C+，特别是在环境方面存在较大争议，仅被华证评级为 BBB，请问你们是否重视改善制造过程中的碳排放问题？未来有没有提升环保表现的具体计划？谢谢!

[English Translation] Hello! I have noticed a considerable gap between your company's ESG performance and that of industry leaders (such as Livzon Group). This year, you were rated CCC

by CTI and C+ by Refinitiv. There is significant controversy regarding the environmental dimension in particular, where you received only a BBB rating from Sino-Securities Index. Does the company place importance on improving carbon emissions during the manufacturing process? Are there any concrete plans to enhance environmental performance in the future? Thank you.

[T2: E Message] 你好，我注意到在汽车生产中，你们有比较多的氮氧化物的排放，这个可能会引起环境部门的注意，另外就是 ESG 评价也不是很高，在业内排名比较低，FTSE 的评分只有 1.4，rks 的评级是 BB，请问董事会有关注到这个话题吗？未来有减排或者其他有利于环境改善的具体措施吗？

[English Translation] I noticed that your automobile production process involves relatively high emissions of nitrogen oxides, which may attract attention from environmental regulators. In addition, your ESG ratings are relatively low within the industry, with an FTSE score of only 1.4 and an RKS rating of BB. Has the board taken note of these environmental issues? Are there any concrete plans for emission reductions or other measures to improve environmental performance?

[T3: S Message] ESG 对企业成功有一定重要性，但贵公司的评级表现欠佳（富时罗素：1.1， 彭博：1.6），在医药生物行业表现靠后。在社会表现上，能否分享下公司是否有关注和支持弱势群体的社会投资计划，如儿童、老年人、残障人士等？是否在其业务决策中考虑社会影响和社会责任？期待 2023 年度 ESG 报告能对这些方面有更多披露！

[English Translation] ESG is critical for corporate success, but your company's rating performance remains weak (FTSE Russell: 1.1; Bloomberg: 1.6), ranking near the bottom of the pharmaceutical and biotech industry. Regarding social performance, could you share whether the company has social investment plans focused on supporting vulnerable groups, such as children, the elderly, or individuals with disabilities? Do you consider social impact and responsibility in your business decisions? I look forward to seeing more disclosure on these aspects in the 2023 ESG report!

[T3: S Message] 董秘您好。我注意到公司 ESG 评分在过去几年一直在很低的水平，其中公司在 MSCI 的 ESG 评级仅为 BB， 彭博 ESG 评分为 3.08， 属于电子行业中下段，有效的社会努力可能给公司带来实质性的收益， 那么公司是否有为解决社会问题和为社会做出积极贡献？ 比如支持教育、医疗或其他社会事业所做的具体举措？

[English Translation] Hello, Board Secretary. I have noticed that the company's ESG ratings have remained at a very low level over the past few years. Specifically, your MSCI ESG rating is only BB and your Bloomberg ESG score is 3.08, placing you in the lower-middle tier of the electronics

industry. Effective social initiatives could potentially generate tangible benefits for the company. Does the firm engage in efforts to address social issues and make positive contributions to society? For example, are there concrete actions to support education, healthcare, or other social causes?

[T4: G Message] 您好，了解到过去几年公司在 ESG 评级方面成绩不是很理想，例如在万得只有 BB，商道融绿只有 B-，不及行业平均水平。尤其公司治理是影响评级的关键环节之一。您是否认为健全的公司治理对公司未来发展至关重要?是否可以考虑制定定量的治理目标和改进计划来提升这一面?

[English Translation] Hello. I think that the company's ESG rating performance has not been strong over the past few years—for example, only BB in Wind and B- in SynTao—falling below the industry average. Corporate governance, in particular, is a critical component affecting these ratings. Do you believe that sound corporate governance is vital for the company's future development? Would you consider establishing quantitative governance goals and improvement plans to enhance this aspect?

[T4: G Message] 董秘您好，我一直对贵公司有投资，最近注意到公司的 ESG 表现，只在华证中得到了 CCC 评级，商道融绿也只有 C+，请问公司如何看待远低于行业平均水平的评分？另外在治理方面，我 11 月份看到新闻报道公司信息披露违规，导致公司在 G 部分仅取得了华证 CCC 评级。请问公司是否计划具体的改进措施并予以高度重视?

[English Translation] Hello, Board Secretary. I have been an investor in your company for some time and recently noticed that your ESG performance remains weak, with a CCC rating from Sino-Securities Index and only a C+ rating from SynTao Green Finance. How does the company view these scores, which are far below the industry average? Regarding governance, I saw news reports in November concerning information disclosure violations, which resulted in a CCC rating in the Governance component from the Sino-Securities Index. Does the company have specific improvement measures in place to prioritize this issue?

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 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?

注意到有股民反映公司存在较大环境风险，大家觉得公司是否应该投资于 ESG 改善？未来 ESG 会怎么发展呢？

[English Translation] I noticed that some shareholders have raised concerns about the company's significant environmental risks. Do you think the company should invest in improving its ESG performance? How do you see the future development of ESG going forward?

Appendix B. 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 C. 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 D. 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 5 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 E. Trends in Alternative Market Response Measures

This appendix assesses the robustness of our main findings on market valuation using three alternative measures. First, to ensure our results are not driven by changes in shares outstanding, we examine share prices 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 Medium-to-Long-Run Model-Free Benchmarks: Share Price and Cumulative Returns

To assess the sensitivity of our results to the choice of valuation metric, we replicate our baseline analysis using two alternative medium-to-long-term outcomes: the natural logarithm of the daily closing price of tradable A-shares and the cumulative log return. Table A10 presents these DiD estimates (Columns 3–6) alongside our baseline market capitalization results (Columns 1–2).

The results strongly corroborate our primary findings. As shown in Columns 3 and 5, the aggregate average treatment effect remains statistically indistinguishable from zero across all specifications. However, when disaggregated by treatment arm, the estimates mirror the heterogeneous patterns observed in our main analysis. Specifically, inquiries about environmental issues yield a statistically significant increase of approximately 2.1% to 2.2% in both share price and cumulative returns (Columns 4 and 6). These coefficients are slightly larger in magnitude and higher in statistical significance ($p < 0.01$) than the 2.0% effect observed for market capitalization ($p < 0.1$). Similarly, governance inquiries exert a consistent negative impact of approximately 1.2% to 1.3% across these alternative measures. These comparisons suggest that our primary choice of market capitalization provides conservative estimates of the intervention's market impact and that the documented divergence is not an artifact of a specific 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:

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

Fama-French Five-Factor Model:

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

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:

$$AR_{i,t} = R_{i,t} - E[R_{i,t}] \quad (3)$$

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

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

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 A14.

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 market capitalization. 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 F. 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.[2]

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.

[2] We abstract from direct productivity benefits to isolate the signaling mechanism. This assumption is motivated by the empirical observation that listed firms in China exhibited limited proactive ESG engagement prior to the intervention. If ESG activities were intrinsically productivity-enhancing, profit-maximizing firms would have strong incentives to adopt them unilaterally, regardless of external demand pressure. That said, our qualitative predictions remain robust to relaxing this assumption: even if ESG inputs contribute directly to production, the equilibrium sorting holds as long as high-productivity firms retain a comparative advantage in generating ESG outcomes (i.e., the single-crossing property is satisfied). Under this more general specification, the model yields identical comparative statics regarding firm productivity, information transparency, and investor composition.

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:

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

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:

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

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:

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

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 G. 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:

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

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

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

where $u_{it}(\beta_l, \beta_k, \beta_m) = \omega_{it} - E\left(\omega_{it}|\omega_{i,t-1}\right)$. 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 H. 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.

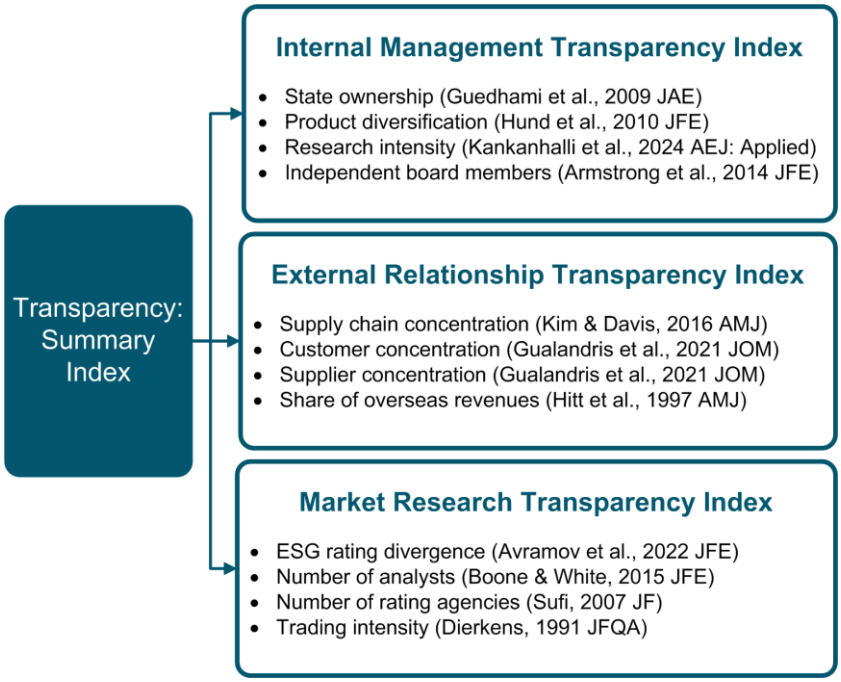
Internal Management Transparency Index: The internal management transparency index reflects the accessibility and clarity of information related to a firm's governance and operational decisions. Drawing on established metrics from the literature, the index incorporates four components. First, **state 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.[3] 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).

[3] 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 I. 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 J. Multiple Hypothesis Testing Adjustments

Given the comprehensive nature of our experiment, we examine a rich set of outcome variables ranging from online response quality to offline corporate actions and market valuations. This raises the potential concern that some statistically significant results could be driven by chance (Type I error) due to multiple hypothesis testing.

To address this concern, we implement the Benjamini and Hochberg (1995) procedure to control the False Discovery Rate (FDR). We prioritize the FDR approach over Family-Wise Error Rate (FWER) methods (such as the Bonferroni or Holm corrections) for two reasons. First, FWER methods are often overly conservative for field experiments with numerous outcomes, leading to a substantial loss of statistical power and potentially masking true treatment effects. Second, many of our outcome variables are conceptually correlated (e.g., response length and sentiment, or ESG ratings from different agencies), and FDR approaches are better suited to preserve power structure under such dependence structure.

We group our 25 primary outcome variables into three conceptually distinct "families" based on the underlying economic agents and the nature of the responses:

1) Online Responses (Family 1, m=14): This family includes metrics of communicative quality derived from corporate answers on the Q&A platforms (e.g., length, sentiment, ESG-specific vocabulary). These represent the most immediate "supply-side" communicative adjustments.

2) Offline Actions (Family 2, m=8): This family encompasses substantive real-world corporate behavioral changes that occur offline, such as the issuance of standalone ESG reports and ESG-related discourse in institutional communications.

3) Market Valuations (Family 3, m=3): This family captures the equilibrium market reactions to different dimensions of ESG messages (Environmental, Social, and Governance).

Within each outcome family, we rank p-values in ascending order and compute FDR-adjusted q-values using the standard step-up Benjamini–Hochberg procedure, enforcing monotonicity. This approach controls the expected proportion of false rejections within each family while remaining robust to correlated outcomes, which are common in corporate disclosure, ESG, and market-response settings.

Table A25 presents the original p-values alongside the FDR-adjusted q-values. The results largely confirm the robustness of our primary findings:

1) Online Responses: All 14 metrics in this family remain highly significant after FDR adjustment. Specifically, indicators of answer quality and specific ESG content (e.g., Length, Sentiment, and ESG Words) maintain $q < 0.001$, suggesting that the treatment effect on online corporate communication is systematic and not an artifact of data mining across multiple dimensions.

2) Offline Actions: Within this family, the effects on ESG report release, ESG mentions in institutional communications, and disclosure of waste generation information remain statistically significant at the 5% level ($q = 0.024$). This confirms that the demand shocks successfully induced substantive corporate actions beyond mere "online talk." However, the marginal effect on Syntao ESG ratings and two other environmental disclosure indicators ($p = 0.141$) loses significance after the adjustment, suggesting that while firms improve their ESG behaviors, these changes may not yet have translated into comprehensive reporting and third-party rating upgrades within our observation window.

3) Market Valuations: In the Market family, the positive valuation effect of Environmental (E) messages ($p = 0.063$) yields an FDR-adjusted adjusted q-value of 0.188. This increase is mechanically driven by both the moderate magnitude of the raw p-value and the inclusion of null effects for S and G messages. While statistical significance is attenuated after adjustment, the persistent divergence in market trajectories for E messages relative to S and G messages reinforces our interpretation of dimension-specific investor pricing.

Appendix K. Additional Tables and Figures

Panel A: Shenzhen Platform



(Original)

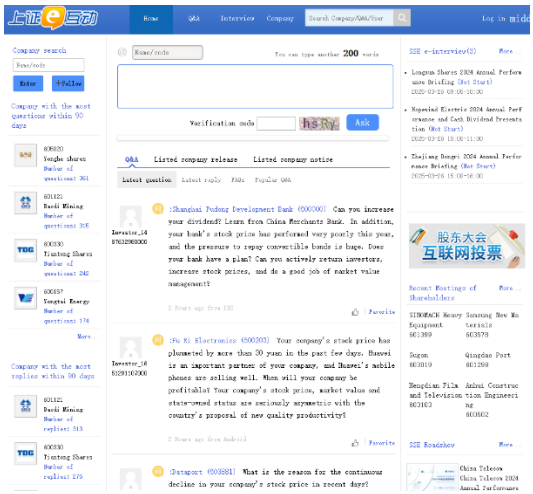


(English Translation)

Panel B: Shanghai Platform



(Original)

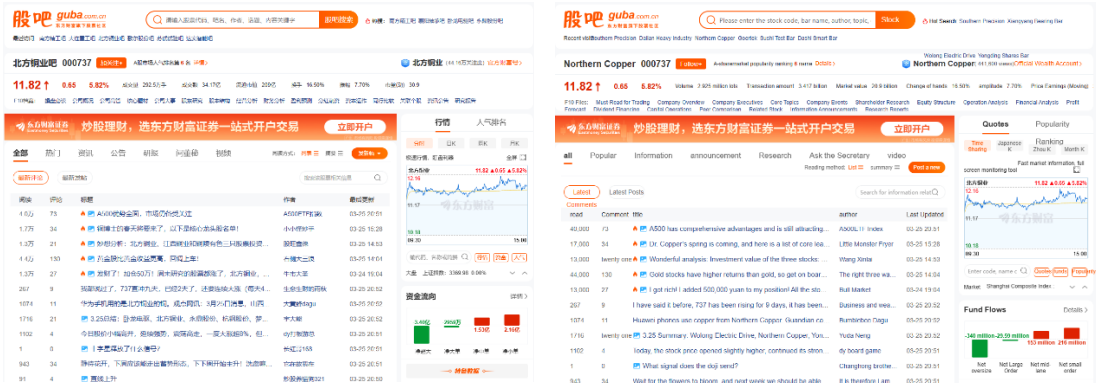


(English Translation)

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

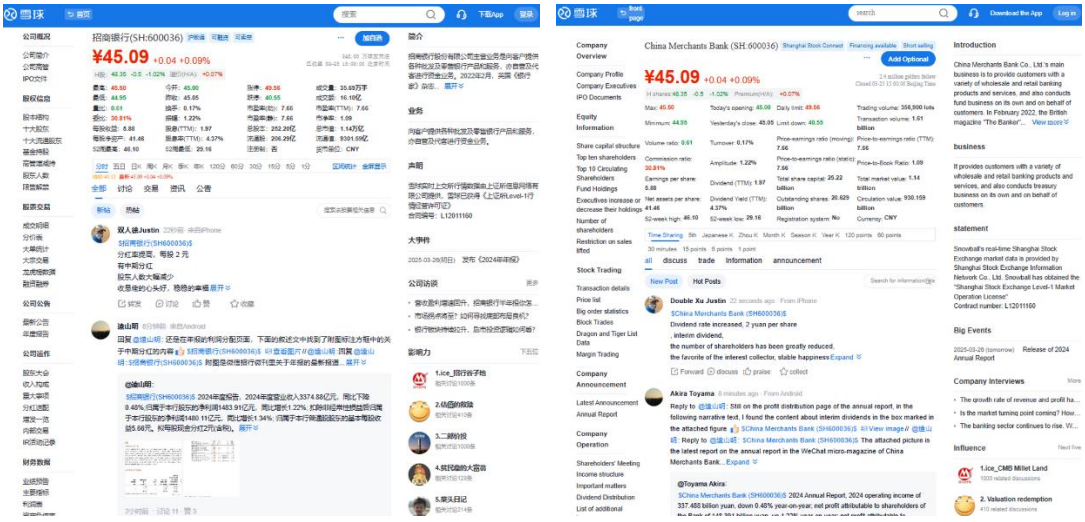
Notes: This figure shows screenshots of the homepages of two online Q&A platforms established by the Shenzhen and Shanghai Stock Exchanges. Apart from platform statistics and announcements on the sides, the main part of the window presents the latest Q&A interactions between investors and firms. The 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)

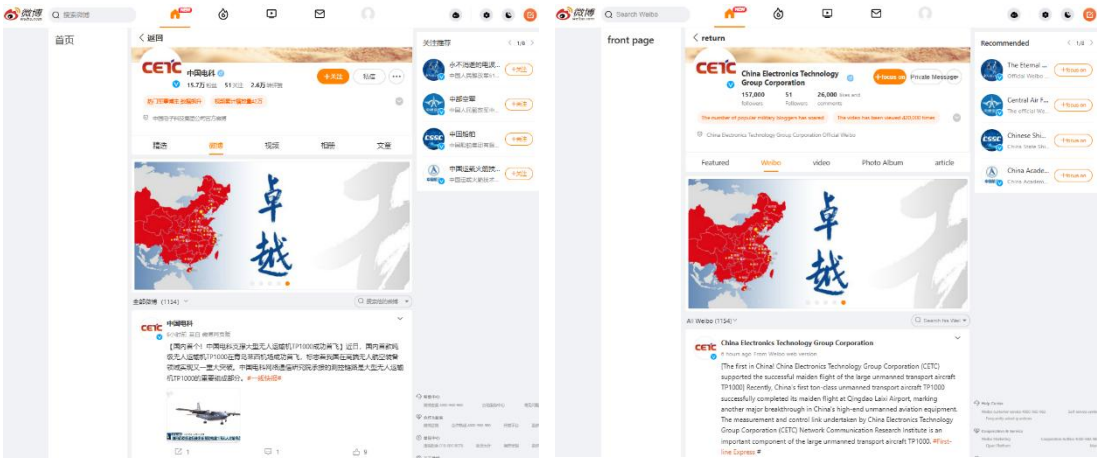
Panel B: Xueqiu (xueqiu.com)



(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.

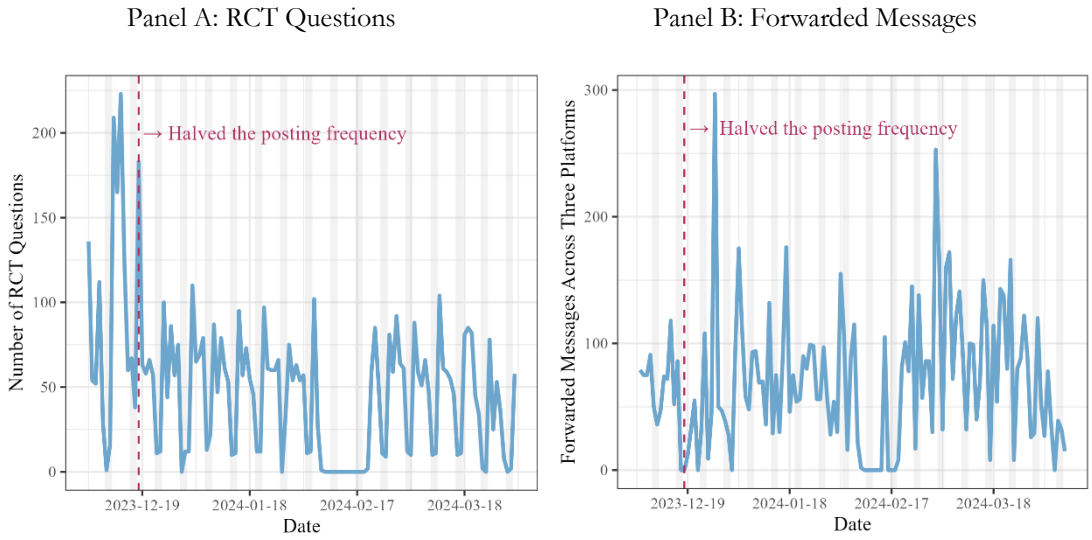
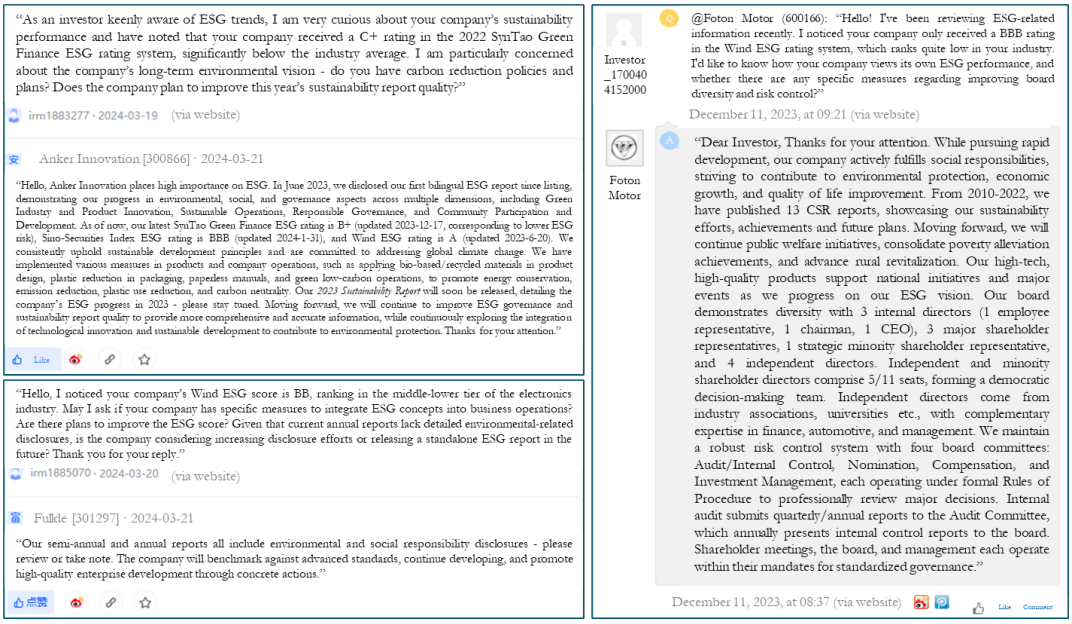


Figure A4. Frequency of RCT Questions by Day

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.



(Original)



(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.

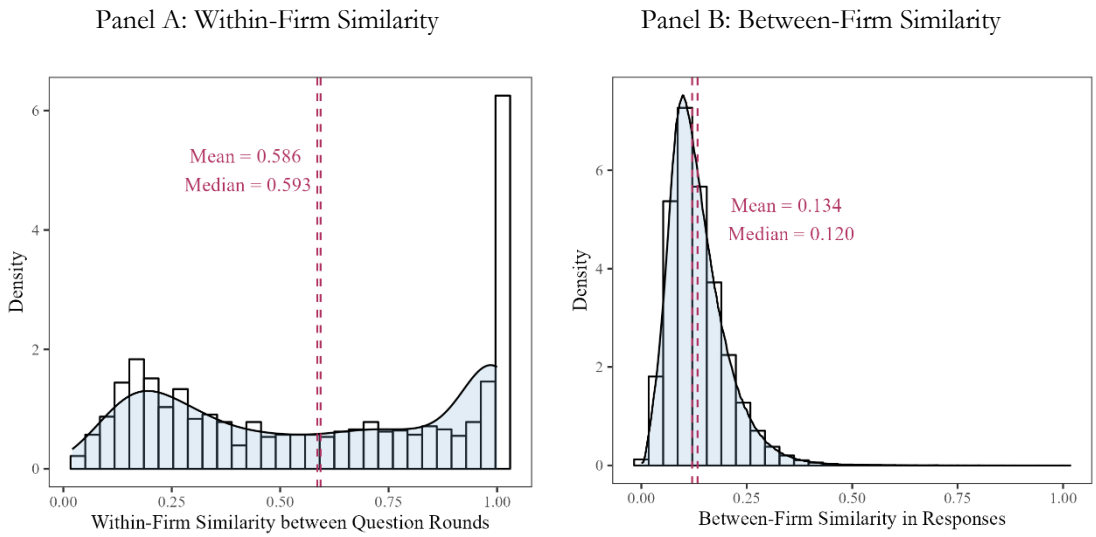


Figure A6. Similarity of Firms' Online Responses

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.

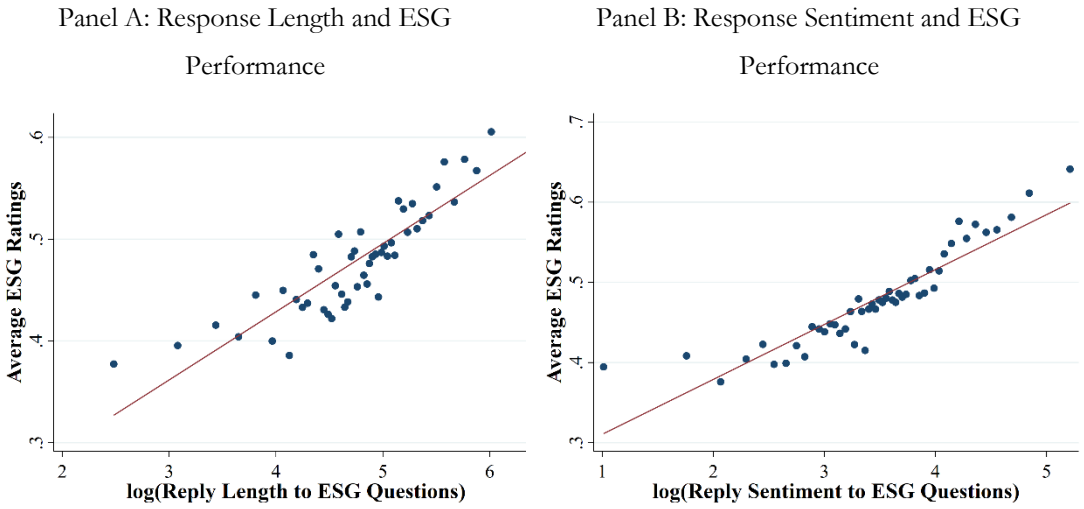
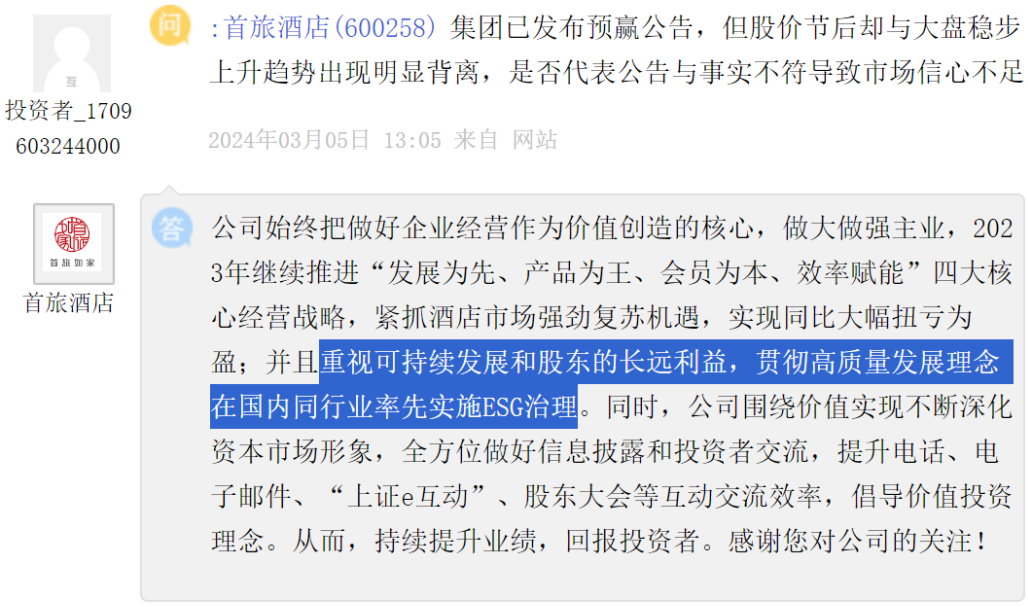
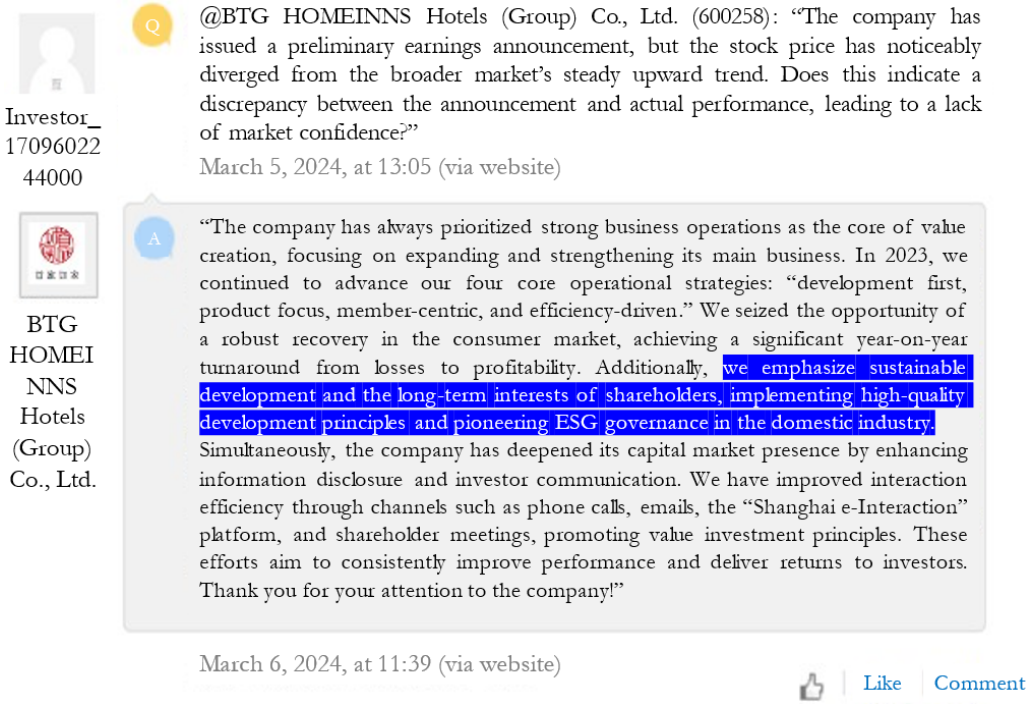


Figure A7. Correlation between Firms' Response Quality and ESG Performance

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.



(Original)



(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."

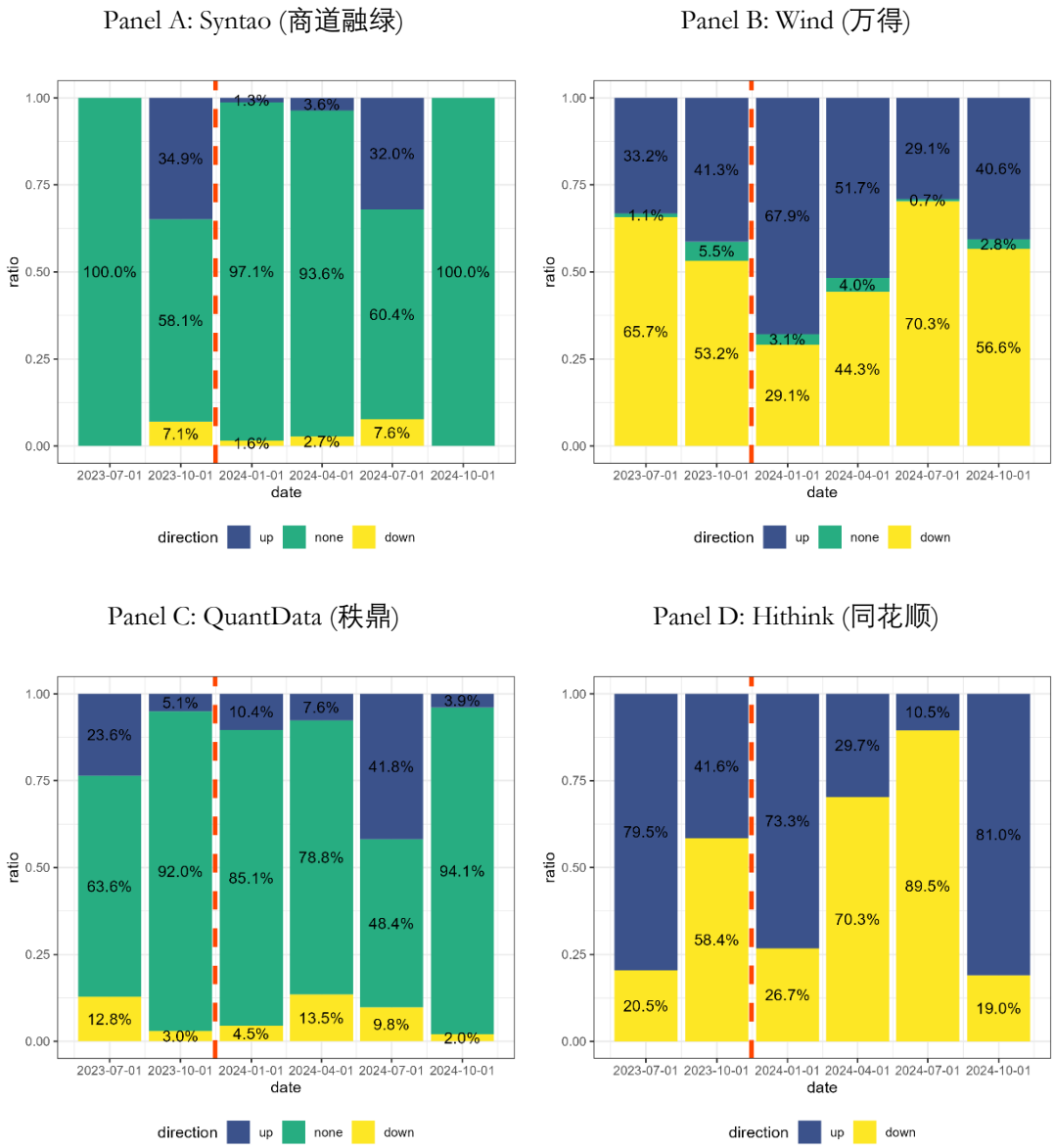


Figure A10. Update Frequency of ESG Ratings

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.

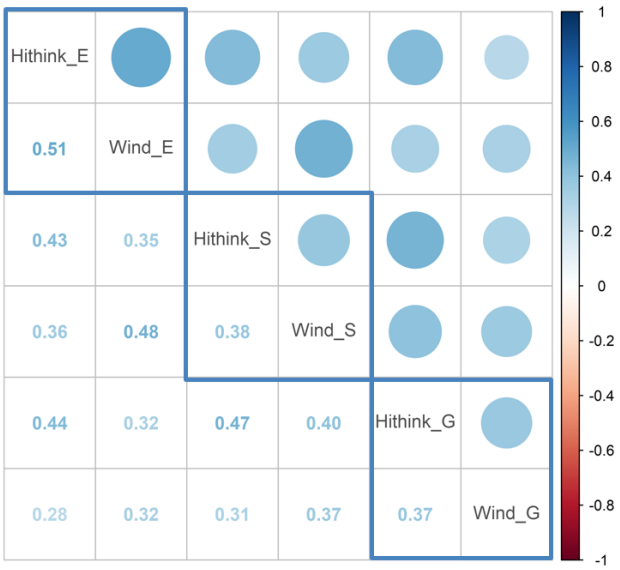


Figure A11. Correlation of E/S/G Ratings Across Rating Agencies

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.

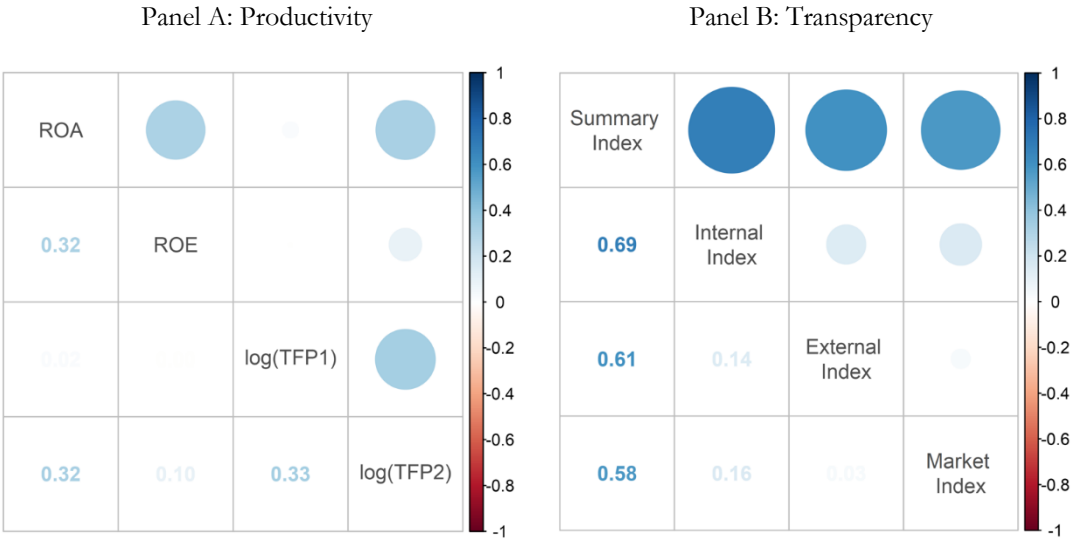
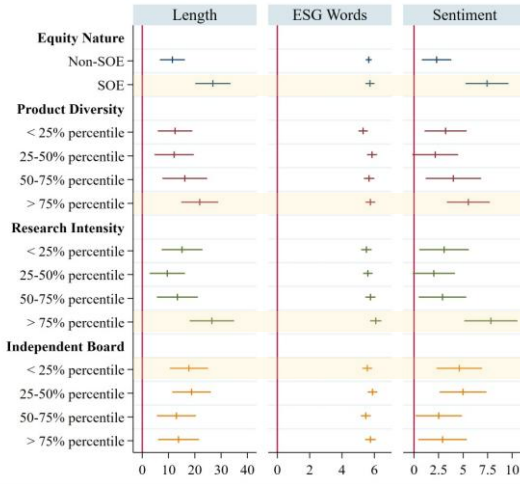


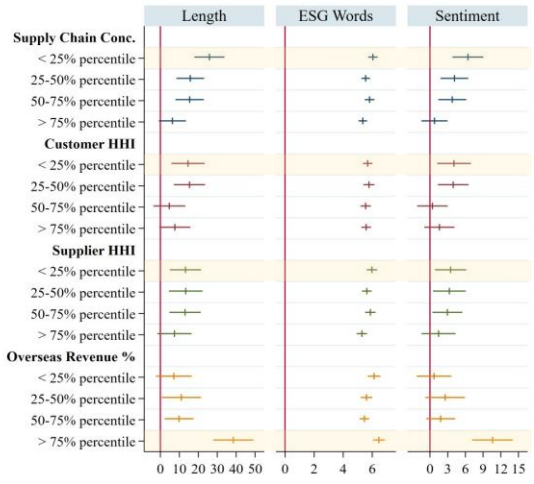
Figure A12. Correlation of Firm Productivity and Transparency Measures

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

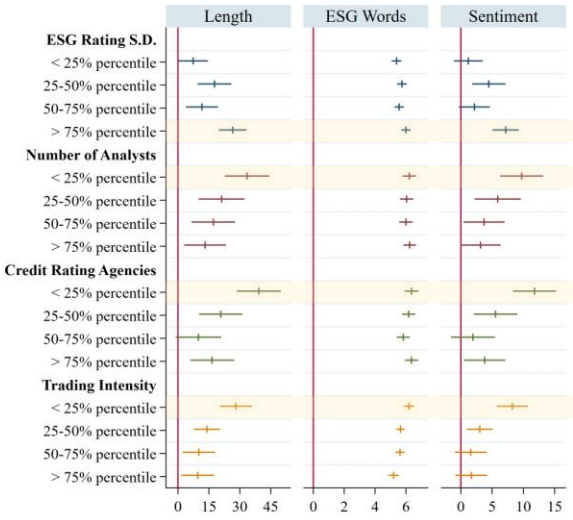


Figure A13. Heterogeneity of Responses Across Transparency Indicators

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.

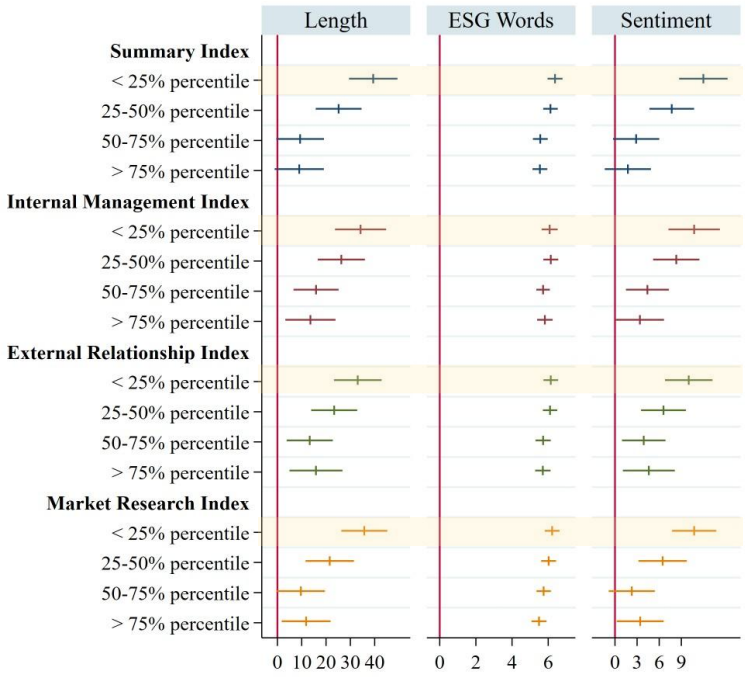
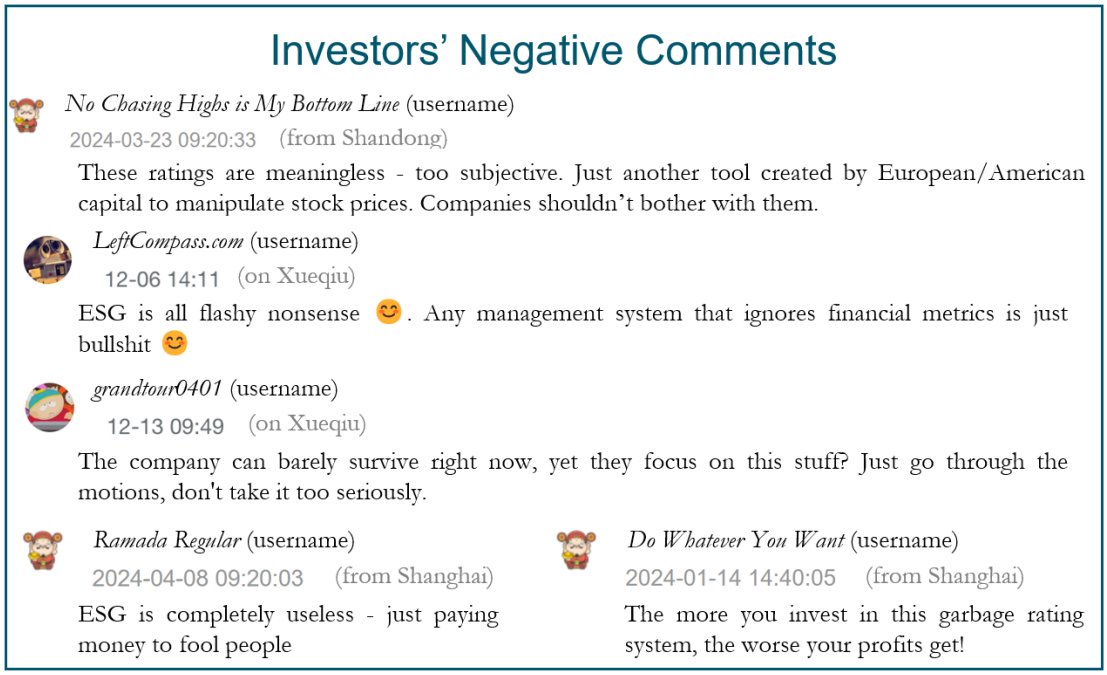


Figure A14. Robustness of Responses Heterogeneity after Controlling for ROA

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 A15. 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)

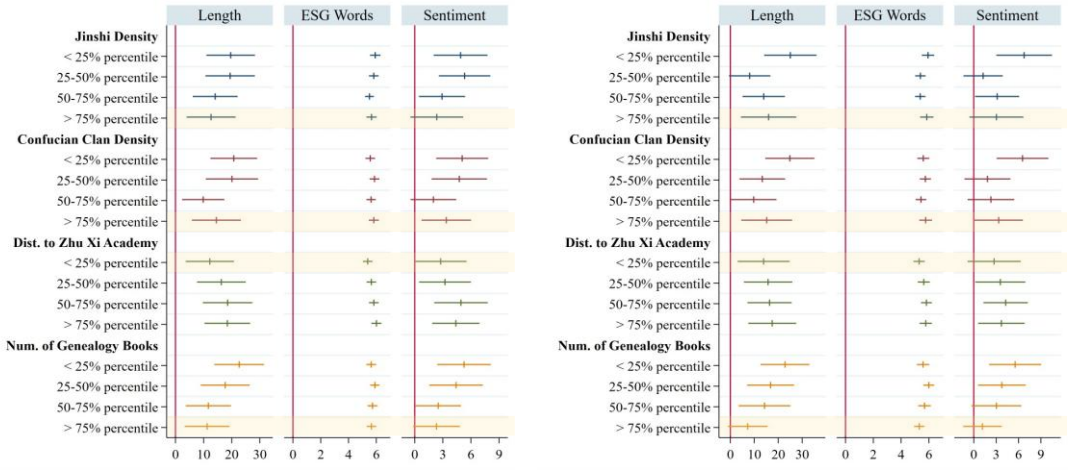


Figure A16. Heterogeneity of Responses Across Alternative Cultural Factors

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) Length	(2) Sentiment	(3) ESG Words	(4) E Words	(5) S Words	(6) 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) Length	(2) Sentiment	(3) ESG Words	(4) E Words	(5) S Words	(6) 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) Length	(2) Sentiment	(3) ESG Words	(4) E Words	(5) S Words	(6) 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)	(2)
	Answer Spillovers	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 Main Offline Actions

	ESG Reports	Communications	Environmental Information Disclosure			ESG Ratings			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	Release Dummy	Mention ESG	Emissions	Waste Generation	Water Consumption	Syntao	Wind	QuantData	Hithink
Post * Treat	2.754***	1.948***	2.706*	4.425***	2.728*	1.045*	0.188	0.475	0.147
	(1.017)	(0.735)	(1.616)	(1.644)	(1.613)	(0.599)	(0.160)	(0.343)	(0.096)
Control Mean	25.104	1.504	29.618	16.409	14.286	45.141	59.159	49.213	63.810
Observations	33,894	11,458	28,719	28,719	28,719	32,946	33,038	32,751	33,170
R-Squared	0.754	0.660	0.539	0.483	0.469	0.815	0.815	0.863	0.920
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	No	Yes	Yes	Yes	No	No	No	No
Quarter FE	No	No	No	No	No	Yes	Yes	Yes	Yes
Industry-Day FE	No	Yes	No	No	No	No	No	No	No

Notes: This table reports average treatment effect estimates of our experiment on firms' main offline ESG-related actions based on Equations (2) and (3). The dependent variables include the release of ESG reports, mentions of ESG during institutional investor communications, three indicators of environmental information disclosure, and quarterly ESG ratings from cited and uncited agencies. 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. Columns 6-7 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. Firms' Aggregate Supplemental Offline Actions

	Carbon Emission Intensity			Pollution Violation		Media Coverage		Others			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
	Scope 1 + 2	Scope 1	Scope 2	NO_X	SO_2	Regulation Violation	Supply Chain Issues	Government Procurement	Regulation Violation	Litigation and Arbitration	Green Patents
Post * Treat	-2.393*	-1.165**	-2.283*	-1.456**	-1.016	-0.252*	-0.033	0.013	-0.001	0.005	-0.015
	(1.340)	(0.546)	(1.292)	(0.693)	(0.910)	(0.134)	(0.042)	(0.030)	(0.018)	(0.020)	(0.012)
Control Mean	10.170	5.858	3.888	3.639	3.712	0.705	0.133	0.424	0.263	0.380	0.487
Observations	2,827	1,908	1,969	115,319	106,816	1,464,707	1,464,707	9,324	28,098	21,870	34,897
Firm Coverage	653	457	470	522	471	4,852	4,852	1,036	3,122	2430	4691
R-Squared	0.696	0.863	0.354	0.364	0.389	0.029	0.026	0.483	0.195	0.291	0.569
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	No	No	No	No	Yes	Yes	Yes	Yes
Quarter FE	No	No	No	No	No	No	No	No	No	No	No
Industry-Day FE	No	No	No	Yes	Yes	Yes	Yes	No	No	No	No

Notes: This table reports average treatment effect estimates of our experiment on firms' supplemental offline ESG-related actions based on Equations (2) and (3). The dependent variables include carbon emission intensities (transformed using the inverse hyperbolic sine function to account for near-zero entries), pollution violation rates for NO_X and SO_2, counts of negative ESG-related media coverage, and annual dummy variables indicating government procurement participation, regulation violations, litigation, and green patent grants. 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 data include firm and year fixed effects, while daily analyses incorporate 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 A10. Aggregate and Heterogeneous Market Responses

	Log(Tradable A-Share Market Value)		Log(Tradable A-Share Market Price)		Cumulative Returns	
	(1)	(2)	(3)	(4)	(5)	(6)
Post * Treat	0.002		0.000		0.000	
	(0.008)		(0.005)		(0.005)	
Post * (ESG Messages)		-0.006		-0.006		-0.006
		(0.010)		(0.008)		(0.008)
Post * (E Messages)		0.020*		0.022***		0.021***
		(0.011)		(0.008)		(0.008)
Post * (S Messages)		0.002		-0.002		-0.002
		(0.011)		(0.008)		(0.008)
Post * (G Messages)		-0.010		-0.013		-0.012
		(0.010)		(0.008)		(0.008)
Control Mean	1.522	1.522	2.517	2.517	-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	0.973	0.973	0.978	0.978	0.695	0.696
P Value: ESG=E Messages	-	0.034	-	0.001	-	0.002
P Value: ESG=S Messages	-	0.543	-	0.701	-	0.635
P Value: ESG=G Messages	-	0.738	-	0.449	-	0.498
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 market capitalization at the firm level. Columns 3-6 show additional market response measures using the natural logarithm of daily tradable A-share closing prices 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. Rows labeled "p-value" report results from pairwise t-tests comparing the coefficients on Post * (E/S/G messages) with those on Post * (ESG messages). 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 A11. Heterogeneity of Firms' Online Responses Across Treatments

	(1) Length	(2) Sentiment	(3) ESG Words	(4) E Words	(5) S Words	(6) G Words	(7) Forward-Looking Words	(8) Numbers	(9) Names	(10) Boilerplate	(11) Accounting Words	(12) 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
P Value: ESG=E Messages	0.000	0.006	0.000	0.000	0.003	0.006	0.873	0.002	0.395	0.005	0.013	0.989
P Value: ESG=S Messages	0.003	0.022	0.521	0.028	0.000	0.393	0.171	0.379	0.963	0.400	0.365	0.024
P Value: ESG=G Messages	0.321	0.921	0.294	0.000	0.374	0.000	0.046	0.434	0.437	0.434	0.217	0.007
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. Rows labeled "p-value" report results from pairwise t-tests comparing the coefficients on E/S/G messages with those on ESG messages. 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 A12. Heterogeneity of Firms' Offline Actions Across Treatments

	ESG Reports	Communications	Environmental Information Disclosure			ESG Ratings			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	Release Dummy	Mention ESG	Emissions	Waste Generation	Water Consumption	Syntao	Wind	QuantData	Hithink
Post * (ESG Messages)	2.440	0.685	3.996*	5.401**	4.658**	1.439	0.172	0.500	-0.059
	(1.518)	(1.015)	(2.313)	(2.422)	(2.338)	(0.971)	(0.224)	(0.518)	(0.141)
Post * (E Messages)	3.497**	2.228**	3.478	4.461*	1.025	0.880	0.142	0.843*	0.347**
	(1.529)	(1.047)	(2.291)	(2.386)	(2.339)	(1.165)	(0.235)	(0.507)	(0.144)
Post * (S Messages)	2.109	1.762	1.686	4.681*	2.593	0.932	0.259	0.491	0.158
	(1.505)	(1.089)	(2.441)	(2.431)	(2.411)	(1.196)	(0.227)	(0.509)	(0.147)
Post * (G Messages)	2.975*	3.161***	1.652	3.164	2.746	0.722	0.162	0.057	0.142
	(1.536)	(1.186)	(2.353)	(2.444)	(2.386)	(1.018)	(0.238)	(0.497)	(0.143)
Control Mean	25.104	1.497	29.618	16.409	14.286	45.141	59.159	49.213	63.811
Observations	33,894	11,458	28,719	28,719	28,719	32,946	33,038	32,751	33,170
R-Squared	0.754	0.660	0.539	0.483	0.469	0.815	0.815	0.863	0.920
P Value: ESG=E Messages	0.568	0.214	0.848	0.743	0.192	0.701	0.910	0.581	0.019
P Value: ESG=S Messages	0.857	0.365	0.415	0.805	0.468	0.732	0.741	0.988	0.216
P Value: ESG=G Messages	0.773	0.062	0.395	0.444	0.498	0.593	0.972	0.468	0.243
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	No	Yes	Yes	Yes	No	No	No	No
Quarter FE	No	No	No	No	No	Yes	Yes	Yes	Yes
Industry-Day FE	No	Yes	No	No	No	No	No	No	No

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 release of ESG reports, mentions of ESG in institutional investor communications, three indicators of environmental information disclosure, and quarterly ESG ratings, 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. Rows labeled "p-value" report results from pairwise t-tests comparing the coefficients on Post * (E/S/G messages) with those on Post * (ESG messages). Specifications for yearly and quarterly data include firm and year-quarter fixed effects, while daily analyses incorporate firm and industry-by-day fixed effects. Columns 6-7 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 A13. 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
P Value: ESG=E Messages	0.121	0.671
P Value: ESG=S Messages	0.085	0.416
P Value: ESG=G Messages	0.763	0.146
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. Rows labeled "p-value" report results from pairwise t-tests comparing the coefficients on Post * (E/S/G messages) with those on Post * (ESG messages). 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 A14. Aggregate and Heterogeneous Effects on Cumulative Abnormal Returns

	Fama-French Three-Factor Model						Fama-French Five-Factor Model					
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	CAR[0,4]	CAR[0,4]	CAR[0,9]	CAR[0,9]	CAR[0,20]	CAR[0,20]	CAR[0,4]	CAR[0,4]	CAR[0,9]	CAR[0,9]	CAR[0,20]	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
P Value: ESG=E Messages	-	0.510	-	0.075	-	0.328	-	0.390	-	0.062	-	0.369
P Value: ESG=S Messages	-	0.744	-	0.516	-	0.866	-	0.700	-	0.522	-	0.930
P Value: ESG=G Messages	-	0.833	-	0.783	-	0.939	-	0.976	-	0.759	-	0.940
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. Rows labeled "p-value" report results from pairwise t-tests comparing the coefficients on E/S/G messages with those on ESG messages. 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 A15. Heterogeneity of Firms' Online Responses Across Productivity Measures

	(1) Length	(2) Sentiment	(3) ESG Words	(4) Length	(5) Sentiment	(6) ESG Words	(7) Length	(8) Sentiment	(9) ESG Words	(10) Length	(11) Sentiment	(12) 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
P Value for Q1=Q2	0.022	0.014	0.002	0.064	0.055	0.002	0.737	0.829	0.279	0.052	0.059	0.017
P Value for Q1=Q3	0.017	0.006	0.001	0.103	0.024	0.003	0.148	0.043	0.976	0.004	0.000	0.000
P Value for Q1=Q4	0.003	0.000	0.000	0.000	0.000	0.000	0.004	0.001	0.847	0.000	0.000	0.000
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). Rows labeled "p-value" report results from pairwise t-tests comparing treatment-effect coefficients for the 2nd, 3rd, and 4th quartiles with those for the 1st quartile. 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 A16. Heterogeneity of Firms' Offline Actions Across Productivity Measures

	ESG Reports	Communications	Environmental Information Disclosure			ESG Ratings			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	Release Dummy	Mention ESG	Emissions	Waste Generation	Water Consumption	Syntao	Wind	QuantData	Hithink
Post * Treat	1.756*	1.245	0.821	2.431	1.079	0.604	0.067	0.121	0.103
	(1.018)	(0.809)	(1.671)	(1.709)	(1.644)	(0.619)	(0.164)	(0.347)	(0.097)
Post * Treat * ROA	36.706***	14.733	54.648***	57.798***	47.808***	11.979**	3.994***	12.848***	1.572*
	(6.235)	(9.509)	(11.504)	(13.234)	(10.874)	(5.569)	(1.119)	(2.329)	(0.814)
Observations	33,894	11,458	28,719	28,719	28,719	32,946	33,038	32,751	33,170
R-Squared	0.755	0.660	0.540	0.484	0.470	0.815	0.815	0.863	0.920
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	No	Yes	Yes	Yes	No	No	No	No
Quarter FE	No	No	No	No	No	Yes	Yes	Yes	Yes
Industry-Day FE	No	Yes	No	No	No	No	No	No	No

Notes: This table reports regression estimates of offline actions across productivity measures based on Equation (9). The dependent variables include the release of ESG reports, mentions of ESG during institutional investor communications, three indicators of environmental information disclosure, and firms' ESG ratings from cited and uncited agencies. 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, 3, 4, and 5 include firm and year fixed effects, column 2 includes firm and industry-by-day fixed effects, and columns 6-9 include firm and quarter 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' 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
P Value for Q1=Q2	0.012	0.024	0.336	0.231	0.294	0.556	0.093	0.075	0.937	0.012	0.020	0.514
P Value for Q1=Q3	0.000	0.000	0.000	0.002	0.001	0.215	0.000	0.000	0.077	0.000	0.000	0.037
P Value for Q1=Q4	0.000	0.000	0.000	0.001	0.000	0.398	0.002	0.003	0.048	0.000	0.000	0.001
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). Rows labeled "p-value" report results from pairwise t-tests comparing treatment-effect coefficients for the 2nd, 3rd, and 4th quartiles with those for the 1st quartile. 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 A18. Heterogeneity of Firms' Offline Actions Across Transparency Measures

	ESG Report	Communications	Environmental Information Disclosure			ESG Ratings			
	(1) Release Dummy	(2) Mention ESG	(3) Emissions	(4) Waste Generation	(5) Water Consumption	(6) Syntao	(7) Wind	(8) QuantData	(9) Hithink
Post * Treat	2.664***	1.993***	1.739	3.264**	1.361	0.747	0.174	0.491	0.132
	(1.014)	(0.754)	(1.636)	(1.657)	(1.619)	(0.590)	(0.159)	(0.343)	(0.095)
Post * Treat * Transparency	-7.643***	-0.952	-9.791***	-11.751***	-13.839***	-4.828***	-2.092***	0.744	-0.797***
	(1.410)	(1.286)	(2.362)	(2.372)	(2.366)	(1.180)	(0.248)	(0.487)	(0.138)
Observations	33,894	11,458	28,719	28,719	28,719	32,946	33,038	32,751	33,170
R-Squared	0.755	0.660	0.540	0.484	0.471	0.815	0.816	0.863	0.921
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	No	Yes	Yes	Yes	No	No	No	No
Quarter FE	No	No	No	No	No	Yes	Yes	Yes	Yes
Industry-Day FE	No	Yes	No	No	No	No	No	No	No

Notes: This table reports regression estimates of offline actions across transparency measures based on Equation (9). The dependent variables include the release of ESG reports, mentions of ESG during institutional investor communications, three indicators of environmental information disclosure, and firms' ESG ratings from cited and uncited agencies. 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, 3, 4, and 5 include firm and year fixed effects, column 2 includes firm and industry-by-day fixed effects, and columns 6-9 include firm and quarter fixed effects. Standard errors in parentheses are clustered at the firm level. *** $p < 0.01$, **$p < 0.05$, *$p < 0.1$.

Table A19. 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
P Value for Neg Comments	0.399	0.084	0.552
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. The row labeled "p-value" report results from pairwise t-tests comparing treatment-effect coefficients for firms receiving negative comments to those for firms receiving no negative comments. 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 A20. 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 A21. Market Returns to ESG Responses and Actions

	Log(Tradable A-Share Market Value)								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Post * Treat * (Z-Score of Reply Length)	0.008*	0.012	0.003	0.004	0.003	0.009*	0.009*	0.008*	0.007
	(0.005)	(0.008)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)
Post * Treat * (ESG Improvement)	0.044***	0.004	0.035***	0.017	0.037***	0.030	0.141	0.145***	0.768***
	(0.014)	(0.056)	(0.013)	(0.013)	(0.013)	(0.035)	(0.094)	(0.041)	(0.149)
ESG Improvement Dimension	ESG Reports: Release Dummy	Communications: Mention ESG	Disclosure: Emissions	Disclosure: Waste Generation	Disclosure: Water Consumption	ESG Ratings: Syntao	ESG Ratings: Wind	ESG Ratings: QuantData	ESG Ratings: Hithink
Observations	636,361	206,690	427,020	427,020	427,020	632,653	618,774	618,052	617,570
R-Squared	0.974	0.970	0.977	0.977	0.977	0.975	0.975	0.975	0.975
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry-Day FE	Yes	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) an interaction term between post dummy, treat dummy, and z-scored reply length to measure the marginal returns to above-average online response quality, and (2) an interaction term between post dummy, treat dummy, and 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 A22. Firms' Alternative Signaling Channels

	(1) Advertising Expenditures	(2) Cash Dividends	(3) Charitable Donations	(4) Poverty Alleviation Expenditures	(5) Managerial Shareholdings (Shares)	(6) Managerial Ownership (%)
Post * Treat	-6.084*	-5.656**	-4.414	-3.497	-3.651	-0.049
	(3.344)	(2.696)	(4.382)	(9.709)	(3.159)	(0.266)
Control Mean	1,673.365	1,886.954	1,405.553	557.349	1,859.278	17.877
Observations	15,765	14,641	10,324	2,031	19,069	18,660
Firm Coverage	2,532	2,556	1,979	429	3,082	2,969
R-Squared	0.877	0.782	0.710	0.761	0.905	0.918
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Quarter FE	No	No	No	No	No	No
Industry-Day FE	No	No	No	No	No	No

Notes: This table reports average treatment effect estimates of our experiment on firms' alternative signaling channels based on Equations (3). The dependent variables include advertising expenditures, cash dividends, charitable donations, poverty alleviation expenditures, managerial shareholdings (measured in number of shares), and managerial ownership (measured as the percentage of shares held by management). Continuous variables in columns 1–5 are transformed using the inverse hyperbolic sine function to account for near-zero entries and scaled by 100 for readability. To mitigate the influence of extreme values and substantial within-firm volatility, we exclude the top and bottom 10% of observations and those exhibiting year-to-year changes exceeding fivefold within the same firm. The independent variable is the interaction term between post and treat dummies to measure the average treatment effect. All specifications 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 A23. Heterogeneity of Firms' Online Responses Across Leader Traits

	(1) Length	(2) Sentiment	(3) ESG Words	(4) Length	(5) Sentiment	(6) ESG Words	(7) Length	(8) Sentiment	(9) ESG Words	(10) Length	(11) Sentiment	(12) 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
P Value for Q1=Q2	0.140	0.126	0.002	0.038	0.143	0.066	0.120	0.321	0.075	0.066	0.206	0.015
P Value for Q1=Q3	0.017	0.009	0.003	0.293	0.368	0.001	0.381	0.656	0.020	0.609	0.535	0.016
P Value for Q1=Q4	0.189	0.116	0.000	0.057	0.119	0.000	0.506	0.964	0.058	0.481	0.801	0.074
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). Rows labeled "p-value" report results from pairwise t-tests comparing treatment-effect coefficients for the 2nd, 3rd, and 4th quartiles with those for the 1st quartile. 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 A24. 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
P Value for Q1=Q2	0.408	0.474	0.351	0.024	0.122	0.139	0.196	0.313	0.049	0.897	0.939	0.743
P Value for Q1=Q3	0.802	0.449	0.306	0.207	0.466	0.508	0.339	0.254	0.592	0.230	0.161	0.118
P Value for Q1=Q4	0.011	0.050	0.034	0.125	0.272	0.516	0.346	0.448	0.243	0.880	0.833	0.772
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). Rows labeled "p-value" report results from pairwise t-tests comparing treatment-effect coefficients for the 2nd, 3rd, and 4th quartiles with those for the 1st quartile. 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 A25. Multiple Hypothesis Testing Adjustment Results

Outcome	Family	Coefficient	S.E.	Original P Value	Original Significance	BH-FDR Q Value	BH-FDR Significance
Length	Online	16.089	2.064	0.000	***	0.000	***
Sentiment	Online	3.841	0.657	0.000	***	0.000	***
ESG Words	Online	5.679	0.079	0.000	***	0.000	***
E Words	Online	1.751	0.049	0.000	***	0.000	***
S Words	Online	1.296	0.025	0.000	***	0.000	***
G Words	Online	0.771	0.020	0.000	***	0.000	***
Forward-Looking Words	Online	0.277	0.023	0.000	***	0.000	***
Numbers	Online	-0.604	0.067	0.000	***	0.000	***
Names	Online	-0.649	0.102	0.000	***	0.000	***
Boilerplate	Online	3.247	0.385	0.000	***	0.000	***
Accounting Words	Online	-0.372	0.030	0.000	***	0.000	***
Regulation Words	Online	2.365	0.052	0.000	***	0.000	***
Answer Spillovers	Online	0.018	0.009	0.035	**	0.035	**
Question Spillovers	Online	0.077	0.027	0.004	***	0.005	***
ESG Reports: Release Dummy	Offline	2.754	1.017	0.007	***	0.024	**
Communications: Mention ESG	Offline	1.948	0.735	0.008	***	0.024	**
Disclosure: Environmental Emissions	Offline	2.706	1.616	0.094	*	0.141	
Disclosure: Waste Generation	Offline	4.425	1.644	0.007	***	0.024	**
Disclosure: Water Consumption	Offline	2.728	1.613	0.091	*	0.141	
ESG Ratings: Syntao	Offline	1.045	0.599	0.081	*	0.141	
ESG Ratings: Wind	Offline	0.188	0.160	0.242		0.242	
ESG Ratings: QuantData	Offline	0.475	0.343	0.166		0.187	
ESG Ratings: Hithink	Offline	0.147	0.096	0.124		0.160	
Market: E Messages	Market	0.020	0.011	0.063	*	0.188	
Market: S Messages	Market	0.002	0.011	0.858		0.858	
Market: G Messages	Market	-0.010	0.010	0.349		0.523	

Notes: This table reports results adjusted for multiple hypothesis testing using the Benjamini and Hochberg (1995) False Discovery Rate (FDR) procedure, as detailed in Appendix J. Dependent variables are partitioned into three conceptually distinct families: (1) Online Responses (supply-side communicative adjustments), (2) Offline Actions (substantive corporate behavioral changes), and (3) Market Valuations (equilibrium stock market reactions). Coefficients and standard errors are estimated using the baseline specifications described in Section IV.4. Original P-values refer to the unadjusted significance levels from the primary analysis. BH-FDR Q-values represent the adjusted p-values that control for the expected proportion of false discoveries within each outcome family. Standard errors are clustered at the firm level. Significance levels for both p and q values are indicated by: *** $p, q < 0.01$, ** $p, q < 0.05$, * $p, q < 0.1$.

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