From the Environment to the Market: How Pollution Monitoring Shapes Analysts' Pricing of Environmental Risks*

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Abstract

Pricing firms' environmental risk is central to ensuring that capital is efficiently allocated in the presence of environmental externalities. We examine whether an increase in the salience of pollution information affects the beliefs and valuations of financially sophisticated agents—specifically, financial analysts—regarding the environmental risks faced by firms they cover. Exploiting the staggered rollout of China's ambient air quality monitoring program, we find that when monitoring is introduced in a city, analysts based there become substantially more likely to discuss air pollution in their reports than analysts covering the same firm at the same time but located in cities yet to adopt the program, even though both groups of analysts have access to the same pollution information. Further, analysts' valuations and investment recommendations become systematically related to firms' environmental risk following treatment. Analysts issue more pessimistic earnings forecasts, set lower target prices, issue weaker recommendations, and adopt a more negative tone when covering highly polluting ("brown") firms, while exhibiting the opposite pattern for environmentally friendly ("green") firms. Importantly, stock prices respond negatively to treated analysts' reports on brown firms and positively to their reports on green firms. These price responses do not reverse over subsequent months, and future earnings announcements generate smaller abnormal returns for green and brown firms, indicating that treated analysts' revisions reflect improved incorporation of environmental risk in prices rather than behavioral biases. Our findings suggest that ambient environmental monitoring can serve as a powerful policy tool for incorporating environmental risk into asset prices by increasing the salience of such risk.

Keywords: ambient air quality, pollution monitoring, stock market, equity analysts, firm valuation

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1. Introduction

Environmental risks such as climate change, driven largely by pollution, impose substantial economic costs by damaging physical capital and disrupting productivity (Dell, Jones, and Olken, 2012). Beyond these economic effects, air pollution remains the leading cause of premature mortality worldwide (Kuehn, 2014), highlighting that its consequences extend beyond environmental degradation and generate large social costs that are not borne by individual emitters. Because these damages arise from classic negative externalities, policymakers have increasingly sought interventions that reduce information frictions and improve accountability, including expanded environmental monitoring.[1] Such efforts typically take two forms. The first, ambient environmental monitoring, communicates real-time local pollution levels to the public, enabling individuals to adapt their behavior. Prior research (e.g., Anderson, Hyun, and Lee, 2022; Barwick, Li, Lin, and Zou, 2024) finds that ambient monitoring heightens the salience of pollution, prompting individuals to reduce exposure to the outdoors and spend more on protective products (e.g., masks, air purifiers), ultimately resulting in better health outcomes. The second approach, firm-specific environmental disclosures, aims to inform stakeholders about firms' carbon footprints, with the expectation that greater transparency enables financial markets to more accurately price firms' environmental risk and induces stakeholder pressure that leads firms to internalize the externalities of their emissions (see Giglio, Kelly, and Stroebel (2021), Starks (2023)). A natural question, then, is whether increased pollution salience—such as that generated by ambient monitoring—affects not only individuals' private, adaptive behaviors but also their professional behavior and economic decision-making.

In this paper, we examine whether ambient environmental monitoring influences market participants' perceptions of firms' environmental risk. We focus on a set of financially sophisticated agents whose beliefs directly affect stock prices—financial analysts—and study

[1] A wide range of policies directly target emissions reduction—such as cap-and-trade programs, emission taxes, and technology standards. Our focus, however, is on monitoring and disclosure policies that aim to enhance information about environmental conditions rather than to directly constrain emissions.

how their outputs (e.g., earnings forecasts, target prices) and recommendations respond to a large-scale expansion of China's air pollution monitoring network. In 2012, China launched a nationwide air quality monitoring program that established an extensive network of stations reporting real-time concentrations of six major air pollutants, as well as a composite Air Quality Index (AQI).[2] Importantly, the network was rolled out gradually across cities, generating plausibly exogenous variation in the salience of air pollution for analysts based on their city of residence. We exploit this staggered rollout to identify how heightened pollution salience affects analysts' attention to, and valuation of, firms' environmental risk.

The introduction of monitoring stations led to a sharp and persistent increase in public awareness of air pollution in treated cities. For example, following the rollout, the average number of newspaper articles covering air pollution rose by 160%, and internet searches for terms such as "smog" and "air pollution" among residents of treated cities increased by 37%. These patterns indicate that the program substantially increased the salience of environmental risks and intensified demand for pollution-related information. Importantly, however, the rollout of the monitoring program does not differentially change analysts' access to information: air quality data are publicly available to all analysts regardless of their location.

We predict that financial analysts residing in treated cities, where pollution becomes more salient in their daily environment, assign greater weight to *publicly known* environmental risks when forming their professional judgments about the firms they cover, regardless of firm location. This prediction follows from a large body of work in psychology and economics showing that salient stimuli attract attention and receive disproportionate weight in judgment and decision-making, even when they do not convey new information (Bordalo, Gennaioli, and Shleifer, 2022). In these models, changes in the environment can alter which attributes or risks are most salient, leading decision makers to overweight certain considerations while underweighting others that are equally available but less attention-grabbing. Applied to financial decision-making, this framework implies that heightened salience of environmental

[2]Six common pollutants are particulate matter ($PM_{2.5}$), coarse particulate matter (PM_{10}), ozone (O_3), carbon monoxide (CO), nitrogen dioxide (NO_2), and sulfur dioxide (SO_2).

risks—such as that induced by ambient pollution monitoring—can affect how agents evaluate risk by shifting the weights they place on publicly known information, rather than by changing the information set itself. Consistent with this logic, we hypothesize that off-the-job exposure to ambient environmental conditions affects how analysts weigh public information when assessing firms' exposure to environmental risk (e.g., changes in environmental regulation, consumer preferences, etc.).

To test this prediction, we employ a difference-in-differences (DiD) framework that exploits variation along two dimensions: (1) the location of analysts, and (2) the timing of the monitoring program's rollout across cities. Specifically, our research design compares the change in an analyst's output (e.g., earnings forecasts, stock recommendations, discussion of a firm's polluting activities) for a given firm-year-quarter before vs. after the rollout of the monitoring program in the analyst's city, to the contemporaneous change in the same outputs of another analyst covering the same firm in the same period but located in a city where the monitoring program has not yet been introduced. Because our unit of observation is at the analyst report–firm–year–quarter level, we can control for all firm–year–quarter characteristics that jointly affect the assessments of all analysts covering a firm, while isolating the effect of individual analysts' exposure to ambient environmental information in their city of residence.

Since the rollout is staggered, we follow De Chaisemartin and d'Haultfoeuille (2020) and Baker, Larcker, and Wang (2022) and construct treatment cohorts based on the quarter in which the program is implemented in a city. Specifically, we employ a stacked cohort DiD design that includes Firm × Year-Quarter × Cohort and Analyst × Firm × Cohort fixed effects. The former set of fixed effects controls for all time-varying and time-invariant firm-level factors, including firm's environmental risk, financial performance, disclosure policies, and the disclosure of ambient environmental information in firms' own cities, allowing us to exploit within-firm-year-quarter variation across treated and not-yet-treated analysts to identify the effect of analysts' local exposure to the monitoring program.[3] The latter set of fixed effects controls for the common

[3]China launched its "war on pollution" around 2010 (Greenstone, He, Li, and Zou, 2021), and the ambient air quality monitoring program was one component of this broader strategy to address severe pollution concerns.

characteristics in an analyst's reports of a firm over time (e.g., analyst quality, analyst-firm manager social ties, analyst-firm distance, etc.).

We first show that when the ambient air quality monitoring program is implemented in a city, analysts based in that city become more than twice as likely to discuss air pollution in their reports relative to analysts located in cities where the program has not yet been introduced. In contrast, we find no corresponding change in analysts' discussions of other nonfinancial topics—such as human capital or social issues—suggesting that the increase in pollution-related discussion does not reflect a broader rise in attention to nonfinancial factors, but rather a targeted increase in attention to environmental risks driven by the heightened salience of air pollution.

To better understand this result, we examine the content of analysts' pollution-related discussions. We find that these discussions primarily focus on regulatory risks faced by firms and potential shifts in consumer preferences, as well as the associated implications for firm sales. Analysts rarely mention physical risks or other environmental channels. Taken together, these findings suggest that as pollution becomes more salient, analysts increasingly consider how transition risks may affect firms' cash flows.

We next examine how analysts' discussions of air pollution vary with firms' environmental impact, which we measure using two complementary approaches. The first employs an LLM-based classification that categorizes firms as green (e.g., producers of environmentally friendly goods such as electric vehicles, low emission firms, etc.), brown (e.g., high emission firms, coal-fired plants, etc.), or neutral. The second relies on a government-designated classification of brown firms, defined as firms required to report data on multiple pollutants because they rank

As a result, increases in analysts' attention to environmental risks could, in principle, reflect a nationwide policy shift toward stricter environmental regulation and heightened market-wide awareness of environmental issues, rather than the local increase in pollution salience induced by the monitoring program. Our research design addresses this concern by including Firm × Year-Quarter × Cohort fixed effects, which ensure that comparisons are made among analysts who are subject to the same national policy environment and the same contemporaneous information about how environmental risks affect firms, but who differ in their local exposure to ambient environmental information. Specifically, this fixed effects structure contrasts analyst reports issued for the same firm in the same quarter by analysts located in cities that adopted the monitoring program at different points in time.

among the top emitters in their county (He, Wang, and Zhang, 2020). Using the LLM-based classification, we find that the increase in pollution-related discussion in treated analysts' reports is significantly larger for both brown and green firms than for neutral firms relative to the corresponding change in control analysts' reports. Similarly, using the government-designated classification, we find that the probability that a treated analyst discusses air pollution in her report increases nearly fourfold following treatment for brown firms, compared with an increase of approximately 50% for other firms.

We then test whether and how the monitoring program affects analysts' quantitative outputs by exploiting heterogeneity in the environmental impact of firms. We find that for brown firms, treated analysts' earnings forecasts are more pessimistic, target prices are lower, buy recommendations are weaker, and report tones are negative, relative to the outputs issued by control analysts for the same firm in the same period. The opposite holds true for green firms. Using the government-designated classification, we find that results for brown firms are similar in sign and magnitude to those for firms classified as brown by the LLM-based approach—i.e., treated analysts' earnings forecasts, stock recommendations, target prices, and report tone are more pessimistic than those of control analysts covering the same firm in the same quarter.

To further probe the mechanism underlying these changes in analysts' research outputs, we examine whether treated analysts are more likely to conduct corporate site visits for green and brown firms post-treatment relative to environmentally neutral firms. Prior research suggests that corporate site visits are an important means through which analysts gather information about the firms they cover (Cheng, Du, Wang, and Wang, 2016; Chen, Ma, Martin, and Michaely, 2022). In particular, interactions between managers and analysts during site visits help analysts refine their valuation assumptions, obtain more detailed and contextual information about public announcements, and better understand a firm's strategy. If heightened pollution salience induces treated analysts to collect or process additional information about a firm's environmental risks, we predict that treated analysts are more likely to visit green and brown firms in their coverage

universe. Consistent with our prediction, we find that treated analysts are three (1.5) times more likely than control analysts to visit the green (brown) firms they cover, but are no more likely than control analysts to visit environmentally neutral firms post-treatment.

Finally, we examine whether the changes in analyst report outputs caused by the ambient monitoring program impact the stock prices of the covered firms. We find that the signed market reaction, measured as the three-day cumulative abnormal return around the analyst's report, is lower for brown and higher for green firms when the report is issued by a treated analyst in the post-treatment period, compared with reports issued by control analysts. These results indicate that the stock market moves toward pricing the environmental risk identified by treated analysts. We find no evidence of return reversals over the subsequent one-month or one-year windows, suggesting that treated analysts are correct in their assessment of firms' environmental risks. Moreover, the information content of subsequent earnings announcements for green and brown firms declines significantly post-treatment when a greater number of treated analysts cover the firm, whereas no such decline is observed for environmentally neutral firms. Taken together, the market reaction to analyst reports, absence of subsequent price reversals, and the decline in the information content of earnings announcements following the monitoring program suggest that stock prices incorporate environmental risk information more quickly, thereby improving price efficiency.[4]

We show that the results are robust to several alternative specifications and sample selection criteria. For instance, our results are robust to (i) using a staggered DiD design with two-way fixed effects (rather than the stacked cohort design), (ii) including several time varying controls at the analyst-firm level, (iii) excluding individual treatment cohorts, and (iv) using different approaches to cluster standard errors. In addition, we verify that the increase in air

[4]A potential alternative interpretation of our results is that the monitoring program leads treated analysts to take adaptive measures that reduce their exposure to pollution, which improves their health and cognitive functioning, ultimately resulting in better decision-making and on-the-job performance (e.g., Li, Luo, and Soderstrom, 2020; Dong, Fisman, Wang, and Xu, 2021). However, the absence of a differential market reaction to the reports of treated and control analysts for environmentally neutral firms, as well as the absence of any change in the information content of earnings announcements by neutral firms, suggests that improvements in treated analysts' cognitive functioning are unlikely to explain our findings.

pollution–related discussions by treated analysts post-treatment is robust to (i) excluding reports issued for firms in cities that adopt the monitoring program and (ii) excluding reports issued for firms in the same city as the treated analyst. We also show that our results are robust to using a second identification strategy that focuses on Chinese firms cross-listed in the U.S. or Hong Kong, which receive coverage not only from analysts residing in mainland China but also from foreign analysts. Specifically, our alternative DID design compares the change in air pollution-related discussions by analysts residing in mainland China around the implementation of the program to the contemporaneous change in air pollution-related discussion by analysts residing outside mainland China following *the same cross-listed firm at the same time*. Similar to our primary research design, our regressions include Firm × Year-Quarter and Firm × Analyst fixed effects, enabling us to exploit variation within firm-year-quarter and across analyst-country. We find that our inferences are robust to employing this alternative research design.

This paper makes several contributions. First, we contribute to the literature on the environmental conditions and stock market outcomes. Prior research finds that exposure to pollution and poor ambient conditions impairs the cognitive ability of market participants, including analysts and mutual fund managers, leading to poor decision-making and a decline in their performance on high-pollution and bad weather days (e.g., deHaan, Madsen, and Piotroski, 2017; Huang, Xu, and Yu, 2020; Li et al., 2020; Dong et al., 2021; Li, Massa, Zhang, and Zhang, 2021). This evidence is typically interpreted as showing that adverse environmental conditions distort judgment and reduce performance. We build on this literature by showing that ambient environmental monitoring—holding constant underlying pollution and weather conditions—can instead improve decision-making by financial analysts. Importantly, our evidence suggests that ambient environmental monitoring leads even sophisticated market participants, such as analysts, to produce higher-quality research outputs by more accurately incorporating environmental risks into firm valuations.

Second, prior studies examine the impact of exposure to extreme or abnormal weather events (e.g., hurricanes, floods, heat waves) on investor and manager behavior, arguing that abnormal

weather increases the salience of environmental risks and leads agents to overweight climate risk in their decision-making (e.g., Bordalo, Gennaioli, and Shleifer, 2013; Dessaint and Matray, 2017; Alok, Kumar, and Wermers, 2020; Choi, Gao, and Jiang, 2020; Cosemans and Frehen, 2021; Cakici and Zaremba, 2022). Our study differs along two important dimensions. First, we show that pollution monitoring—unlike extreme realizations of environmental conditions—can serve as a powerful yet low-cost policy lever through which regulators induce even sophisticated market participants to incorporate environmental risks into their decisions. Second, unlike much of the prior literature, our evidence suggests that analysts' responses to heightened pollution salience improve, rather than distort, their research outputs: analysts are correct in incorporating environmental risks into their valuations in response to pollution information, whereas prior studies often find that salient environmental events lead to biased or excessive reactions.

Third, our paper relates to the growing literature on the consequences of environmental news and disclosures. Prior research examines how firm-level environmental disclosures influence firms' decisions and performance (e.g., Chen, Hung, and Wang, 2018; Downar, Ernstberger, Reichelstein, Schwenen, and Zaklan, 2021; Tomar, 2023), as well as the information sets and investment decisions of investors (e.g., Ilhan, Krueger, Sautner, and Starks, 2023). Prior work also examines the pricing of environmental risks (e.g., Bolton and Kacperczyk, 2021; Lubos, Stambaugh, and Taylor, 2022; Bolton and Kacperczyk, 2023; Zhang, 2025; Derrien, Krueger, Landier, and Yao, 2025). Rather than focusing on firm-specific environmental disclosures or the release of environmental news, our analyses hold firm-specific environmental disclosures and news constant and instead exploit variation in the salience of publicly available pollution information to study how market participants' beliefs and valuations respond when the information set is held fixed.

Finally, this paper relates to prior studies exploring the consequences of China's air pollution monitoring program. Prior studies examine the program's impact on individuals' health and adaptation responses to mitigate exposure to high pollution levels, including increasing defensive expenditures such as purchasing health insurance, masks, and air purifiers (Chang, Huang,

and Wang, 2018; Xie, Yuan, and Zhang, 2023; Barwick et al., 2024). We contribute to this literature by showing that ambient monitoring also affects financial markets by changing how environmental risks are priced: by increasing the salience of air pollution, monitoring leads to positive return responses for green firms and negative return responses for brown firms.

In a more closely related study that also examines the effect of pollution monitoring in India on stock market participants, Fisman, Ghosh, Sarkar, and Zhang (2026) find that retail investors' investments in brown stocks are negatively related to local air pollution after the rollout of a pollution monitoring station. We differ from this study in three important respects. First, Fisman et al. (2026) do not examine whether retail investor trading ultimately moves market prices. Second, they do not assess whether retail investors' responses reflect correct incorporation of environmental risk or behavioral overreaction. By contrast, we show that analysts' responses to pollution monitoring are transmitted to prices and do not subsequently reverse, consistent with improved pricing of environmental risk rather than transitory sentiment. Third, Fisman et al. (2026) interpret their results as evidence that greater salience about air pollution leads to changes in retail investors' nonpecuniary preferences (see also Starks, 2023), which manifest as reduced investment in brown stocks. By contrast, our evidence suggests that heightened pollution salience leads to changes in financial analysts' environmental risk assessments, operating through belief updating rather than shifts in tastes or preferences.

2. Background on Pollution Monitoring in China

China's economic growth, together with its dependence on fossil fuels and lax environmental regulation, made it the largest emitter of carbon dioxide (CO_2) and sulfur dioxide (SO_2) by 2010. In the 2000s, daily average concentrations of fine particulate matter ($PM_{2.5}$) were estimated to be five times higher than the guidelines set by the World Health Organization. As such, severe air pollution in large urban centers resulted in public outcry over the absence of any meaningful government response and the lack of public information about pollution. Consequently, China began to move away from prioritizing economic growth over environmental concerns, and reducing air pollution became an important goal of the Chinese

central government (e.g., Greenstone et al., 2021).[5]

Prior to 2012, local environmental bureaus collected data on three pollutants: PM_{10}, SO_2, and NO_2, and submitted them to the Ministry of Environmental Protection (MEP) without validation. The MEP then constructed a daily Air Pollution Index (API) and disseminated such information. However, the environmental bureaus responsible for collecting these data were appointed by local governments, which created a conflict of interest. In particular, the strong incentives for economic growth at the local level along with weak monitoring and enforcement by the central government compromised data quality. Concerns about pollution data quality became salient in 2008 when the U.S. Embassy in Beijing, and later in the U.S. Consulates in Shanghai, Guangzhou, Chengdu, and Shenyang, started tweeting $PM_{2.5}$ readings every hour, and these readings turned out to be significantly higher than official Chinese statistics. Indeed, prior studies find that there was widespread manipulation of pollution data prior to 2012 (e.g., Greenstone, He, Jia, and Liu, 2022).

To effectively monitor local air pollution and gain public trust, the MEP implemented a nationwide monitoring program in 2012. The program contains two major provisions. First, the MEP installed more than 1,600 U.S. EPA-grade pollution monitoring stations across 337 cities, covering 98% of the population in China. Each station is equipped with automated, real-time monitoring devices that continuously track concentrations of six major pollutants ($PM_{2.5}$, PM_{10}, O_3, CO, NO_2, and SO_2). Such automation reduced opportunities for manipulating air quality data because readings from each station are sent to the central government in real time. In addition, discrepancies between different monitoring sites that are geographically proximate would trigger alerts, allowing the central government to further investigate the causes. Prior research finds that the program eliminated opportunities for local governments to misreport air pollution data (Greenstone et al., 2022).

Second, the MEP established a real-time information dissemination system, which directly controls pollution monitors and automatically transmits the pollution data collected to its

[5]In March 2014, Premier Li Keqiang declared a "war on pollution" and called smog "nature's warning against inefficient and blind development."

information center. These data are disseminated via the MEP's website, providing public access to real-time, hourly pollution levels on the six major pollutants for each individual monitoring station. In addition, the MEP allows private parties to access data directly from its website, which spurred a surge in media reports and mobile phone applications that display real-time air quality information.

Under the monitoring program rollout, cities are assigned to three waves based on administrative hierarchies and pre-existing designations, with varying deadlines to implement the program. The official rollout dates specified in the MEP guidelines serve as "deadlines" to implement the policy, but in practice many cities installed monitors prior to the official rollout dates. The exact rollout date for each city was largely determined by the logistical challenges associated with installing monitoring stations and integrating the data-transmitting systems. We manually searched news reports and city yearbooks to identify when pollution information first became available in each of the 17 cities that is home to at least one financial analyst. We define the rollout quarter as the first quarter in which at least one-and-a-half months of pollution information became available.[6] Table 1 reports the list of cities in our sample as well as their respective rollout dates and quarters.

3. The effect of the program on awareness of air pollution

China's real-time pollution monitoring program led to a sharp and abrupt increase in public access to local air quality information, substantially enhancing public awareness of air pollution. To document changes in individuals' information consumption following the program's rollout, we examine its effect on two key outcomes: media coverage of air pollution and internet searches related to air quality. We begin by analyzing changes in media coverage. Specifically, for each city and quarter, we count the number of newspaper articles discussing air pollution in both commercial and state-owned outlets (e.g., *People's Daily*). Articles are identified based on the presence of air pollution–related terms (e.g., "smog," "air pollution") and a reference to a city

[6]Specifically, if the rollout occurs in the first half of a quarter, rollout quarter is coded as one beginning in that quarter; if it occurs in the second half of the quarter, rollout quarter is coded as one beginning in the subsequent quarter.

name. We find that the average number of newspaper articles about air pollution increased nearly ninefold after the program's implementation—from roughly two to 18 articles per city-quarter.

To formally examine the impact of the program's implementation on the frequency of media coverage of air pollution, we employ a stacked difference-in-differences (DiD) design following De Chaisemartin and d'Haultfoeuille (2020) and Baker et al. (2022). The monitoring program was rolled out across 17 Chinese cities with financial analysts over six quarters, staggered between 2012Q1 and 2013Q4. For each adoption quarter, we define the treated group as cities that adopted the program in that quarter, and use cities that adopted it in later quarters as the control group. For instance, cities adopting the program in 2012Q1 constitute the treated group for cohort 1, while cities adopting in quarters 2 through 6 serve as controls for that cohort until their own adoption. Because no later-treated cities are available as controls for cities adopting the system in quarter 6, these cities are excluded from the treated sample. The resulting dataset stacks five cohorts into a single sample, and we estimate the following regression specification using the stacked sample:

$$y_{city,q,c} = \beta \; Treated \; City_{city,c} \times Post_{q,c} + \alpha_{city,c} + \alpha_{q,c} + \varepsilon_{city,q,c} \tag{1}$$

where, *city*, q, and c index cities, calendar year-quarters, and treatment cohort, respectively. In our first analysis, y is *News Coverage*, defined as the number of newspaper articles in a given city-quarter that contain air pollution–related keywords in the title and include a reference to the city in the text. Because *News Coverage* is a non-negative count variable, we estimate the regression using a Poisson specification following Cohn, Liu, and Wardlaw (2022) and Chen and Roth (2024). $Treated\ City_{city,c}$ is an indicator variable that equals one for treated cities in cohort c and zero for control cities in that cohort. $Post_{q,c}$ is an indicator variable that equals one for both treated and control cities in cohort c for quarters following implementation of the monitoring program for the treated cities. $\alpha_{city,c}$ and $\alpha_{q,c}$ represent City × Cohort and Year-Quarter × Cohort fixed effects, respectively. City-Cohort fixed effects absorb time-invariant city-level variables that affect media coverage of air pollution, and Year-Quarter-Cohort fixed

effects control changes in media coverage that are common to all cities in a Year-Quarter. We cluster standard errors at the City-Year level.[7]

Column 1 of Table 2 shows that the coefficient for *Treated City* × *Post* is positive and significant at the 1% level; the coefficient estimate implies that media mentions of pollution increase by 160% on average after the implementation of the monitoring system in a city. Panel A of Figure 1 provides an event-time plot of changes in media coverage in treated cities relative to that in control cities during our sample period. We find no evidence of differential trends in media coverage of pollution in treated and control cities prior to the program rollout but a sharp increase in media coverage about treated cities in the quarters after the program's implementation. These results suggest that the monitoring program significantly increases the frequency of articles related to air pollution in the media, thereby enhancing public awareness of air pollution.

It is important to note that media coverage not only increases the salience of air quality issues but also plays an essential educational role, informing the public about the sources, severity, and health as well as regulatory consequences of air pollution. Moreover, such coverage often stimulates broader public discourse on social media platforms and blogs, where individuals share, interpret, and debate pollution-related content. For instance, on February 28, 2015, the Chinese state newspaper *People's Daily* released the environmental documentary *Under the Dome* by journalist Chai Jing, which spotlighted China's air pollution challenges. Within a week, the film had been viewed over 300 million times and sparked widespread discussion on Chinese social media platforms (Branigan, 2015; Shao, 2015), illustrating the capacity of traditional media to catalyze large-scale public engagement and secondary online debate.

To provide further evidence that the monitoring program affects awareness about air pollution, we examine whether internet searches for air pollution–related keywords increase following the program's implementation. We measure the number of searches for "smog" and

[7]We cluster at the City-Year level rather than the City-level because our sample includes only 17 cities, which is potentially too few clusters to obtain unbiased standard errors (Petersen, 2008). However, our inferences are robust to clustering standard errors at the City-level (untabulated).

"air pollution" on Baidu, China's most widely used search engine, at the city-day level. On average, daily searches increased by 450%, rising from 48 pre-program to 264 post-program. To formally test this effect, we change the dependent variable in Equation 1 to *Internet Search*, defined as the average number of daily searches for air pollution–related keywords in each city-year-quarter. Given that *Internet Search* is a count variable, we estimate the model using a Poisson specification (Cohn et al., 2022).

Column 2 of Table 2 presents the results.[8] We find that the coefficient for *Treated City* × *Post* is positive and significant at the 5% level, indicating that the introduction of the monitoring program leads to an increase in internet searches for information about air pollution—the coefficient estimate implies a 37% increase in search volume on average. Panel B of Figure 1 shows the event-time change in internet searches by individuals located in treated cities relative to those by individuals located in control cities around the program's implementation. We find that internet searches by individuals in treated and control cities trend similarly prior to the program implementation but sharply diverge in the quarters following the program's implementation. Overall, our findings demonstrate that individuals seek more information about air pollution after the monitoring program is implemented in their city. Our evidence is consistent with that in Barwick et al. (2024), who find that the program's implementation led to a nationwide increase in newly released mobile phone applications that track air pollution, and increased concern about environmental issues among Chinese families (using national surveys).

4. Research design and data

4.1. Research design

To examine whether exposure to ambient environmental information influences financial analysts' consideration of environmental risks in firm valuation, we employ a stacked cohort difference-in-differences (DiD) design. Our approach leverages the staggered rollout of China's pollution monitoring program across cities, combined with geographic variation in the

[8]The sample size in Column 2 of Table 2 is smaller than that in Column 1 because the internet search dataset begins in 2011, while our *News Coverage* sample starts in 2010.

locations of financial analysts who cover the same firm at the same time. While the rollout of the pollution monitoring program increased the availability and timeliness of publicly reported air quality data, these data were equally accessible to all analysts (and the public at large), irrespective of their location. Accordingly, the program did not differentially alter analysts' access to pollution information. Instead, because monitoring infrastructure became operational at different times across cities, analysts' local exposure to and the salience of air quality information varied based on their city of residence. In particular, even when covering the same firm, analysts residing in cities that adopted monitoring earlier experienced a sharper increase in the salience of pollution information, despite having access to the same underlying pollution data as analysts elsewhere. This cross-sectional and temporal variation in local salience allows us to identify the causal effect of heightened ambient environmental salience—holding firm-level fundamentals and information access constant—on analysts' perceptions of firms' environmental risk and valuation.

Our primary identifying assumption is that, conditional on firm-time and analyst-firm fixed effects, the introduction of pollution monitoring does not differentially alter analysts' firm-specific information about the firms they cover (at least for firms *not* headquartered in the same city as the analyst).[9] In other words, while analysts may differ in their overall information levels, we assume that the change in firm-specific information around the rollout of monitoring is no different across treated and control analysts covering the same firm. Thus, any differential changes in analysts' outputs, such as the content of their reports, earnings forecasts, or stock recommendations, can then be interpreted as reflecting location-based variation in the salience of ambient environmental information, rather than differential changes in the underlying firm-specific information about the covered firm.

Our data comprise 17 unique cities in which at least one financial analyst resides. These

[9] We recognize that proximity between analysts and the firms they cover can affect information acquisition costs (e.g., Bae, Stulz, and Tan, 2008; Chen et al., 2022). However, any cross-analyst heterogeneity in information levels should be absorbed by our fixed effects and DiD regression design. Nevertheless, in Table B16 in the Internet Appendix, we verify that our results are not explained by differences in the distance between analysts and the covered firms.

cities adopted the pollution monitoring program over six distinct quarters staggered between 2012Q1 and 2013Q4. Panel A of Figure 2 shows the distribution of analyst reports over time for each adoption quarter. In each adoption quarter, we define treated analysts as those residing in cities that adopt the program in that quarter, and use analysts in cities that adopt the program in later quarters as the control group. For example, analysts in cities that adopt the program in 2012Q1 are designated as treated analysts in cohort 1, while analysts in later-adopting cities (quarters 2 through 6) serve as controls for that cohort until their own adoption. Panels B and C of Figure 2 present the distribution of analyst reports over time for treated and control analysts in cohorts 1 and 2, respectively. We do not use analysts from the final cohort as treated observations in our tests because no later-treated analysts remain to serve as controls. Thus, our sample includes five cohorts stacked into a single dataset. By comparing treated analysts only to not-yet-treated analysts at the time of adoption, our research design mitigates concerns about heterogeneous dynamic treatment effects (e.g., De Chaisemartin and d'Haultfoeuille, 2020; Baker et al., 2022).

We estimate regressions of the following form using the stacked dataset:

$$y_{i,j,q,c} = \beta \, Treated_{i,c} \times Post_{q,c} + \alpha_{j,q,c} + \alpha_{i,j,c} + \varepsilon_{i,j,q,c} \tag{2}$$

where, i, j, q, and c index analysts, firms, calendar year-quarters, and treatment cohorts, respectively. $y_{i,j,q,c}$ is one of several outputs contained in analyst i's report issued for firm j in period q (discussed in more detail below). $Treated_{i,c}$ equals one for treated analysts in cohort c and zero for control analysts. $Post_{q,c}$ equals one beginning in the first quarter in which treated analysts in cohort c receive the treatment, i.e., when the monitoring program is implemented in the treated analyst's city, and remains one thereafter.[10] Figure 2, Panels B and C, illustrates the observations for which we set *Treated* and *Post* variables equal to one for cohorts 1 and 2, respectively.

The terms $\alpha_{j,q,c}$ and $\alpha_{i,j,c}$ denote Firm × Year-Quarter × Cohort and Analyst × Firm × Cohort fixed effects, respectively. Firm-Year-Quarter-Cohort fixed effects control for all

[10] Our fixed effects subsume the main effects of *Treated* and *Post*.

time-varying and time-invariant firm characteristics within a given quarter, including the firm's emission profile, financial performance, growth prospects, shareholder base, disclosure policies, etc. These fixed effects also control for ambient environmental information disclosed in the firm's city as part of the monitoring program, and time-series variation in the discussion of air pollution that is common across all analysts covering the same firm during that period. As such, our research design exploits within-firm-year-quarter and across-analyst variation in city of residence to identify the causal effect of the monitoring program on analysts' output.

Firm-Analyst-Cohort fixed effects control for time-invariant characteristics of each firm–analyst pair, including persistent matching patterns and analyst-specific traits.[11] The coefficient of interest in Equation 2 is β, which captures the differential pre–post change in outputs and firm-value assessments by treated analysts relative to control analysts covering the same firm in the same period.

We initially examine whether analysts discuss firms' air-polluting activities in the text of their reports. To do so, we instruct a generative large language model (*DeepSeek-R1*) to identify whether these reports explicitly discuss air quality,[12] as defined by the Sustainability Accounting Standards Board (SASB), which developed industry-specific standards for sustainability-related financial disclosures.[13] We provide more details on the performance of the large language model and analyses to validate our proxy in Internet Appendix C and present several examples of air pollution discussions in analyst reports in Internet Appendix D. We also verify that our

[11] Firm-Analyst-Cohort fixed effects also absorb the distance between the firm and the analyst. If an analyst moves from one city to another during our sample period, we assign the analyst to the first city that implements the monitoring program to avoid coding them as treated more than once, effectively assuming a single location. Our results are robust to excluding analysts with more than one reported city during our sample period (untabulated).

[12] We convert the analyst reports in our sample from PDF to plain text using PyMuPDF4LLM, a tool optimized for large language models, that enables accurate extraction of textual content while preserving the original layout and paragraph structure.

[13] In 2022, SASB standards and projects were integrated into the International Sustainability Standards Board (ISSB), which is now responsible for their ongoing development within the global sustainability disclosure ecosystem. The SASB defines air quality as addressing "management of air quality impacts resulting from stationary (e.g., factories, power plants) and mobile sources (e.g., trucks, delivery vehicles, planes) as well as industrial emissions. Relevant airborne pollutants include, but are not limited to, oxides of nitrogen (NO_x), oxides of sulfur (SO_x), volatile organic compounds (VOCs), heavy metals, particulate matter, and chlorofluorocarbons. The category does not include GHG emissions, which are addressed in a separate category." For more details, see https://sasb.ifrs.org/standards/materiality-finder/.

inferences are robust to using an alternative proxy based on the methodology developed by Lin, Shen, Wang, and Yu (2024), who employ a word embedding model to create a dictionary for quantifying pollution disclosure. Specifically, we construct an indicator variable, *Air Pollution Discussed–Dict*, that equals one if the analyst report contains air pollution-related words and phrases from their pollution dictionary.[14]

We also examine several quantitative outputs produced by analysts, including their earnings per share (EPS) forecasts, stock recommendations, target prices, and report tone. Finally, we examine the market reaction to analyst reports to test whether changes in report content translate into changes in investor perceptions of firm value.

4.2. Sample selection and descriptive statistics

Table B1 in the Internet Appendix outlines our sample selection process. We begin with 217,510 analyst reports issued between 2010Q1 and 2015Q4 for firms listed on the Shenzhen and Shanghai Stock Exchanges, obtained from the CnOpenData database, which compiles the textual content of analyst reports from brokerage firms across mainland China. This sample period spans eight quarters before the first adoption quarter in 2012Q1 and eight quarters after the final adoption quarter in 2013Q4. To obtain information on analysts' EPS forecasts and stock recommendations, as well as their characteristics (e.g., age), we merge each report with data from the Chinese Research Data Services (CNRDS) platform using broker names, analyst names, covered firm names, and report dates.[15] Next, we manually identify analyst locations using the area code from the phone number provided in each report and exclude any reports lacking this information.[16] To analyze changes in analysts' discussions of pollution around the

[14] Lin et al. (2024) develop a *Pollution and Waste* dictionary that captures air quality along with other topics such as waste management and water treatment. Since our focus is specifically on air quality, we select a subset of keywords from their dictionary that pertain to air quality. Specifically, we instruct *DeepSeek-R1* to assess the relevance of each keyword based on the SASB's definition of air quality. We retain only keywords for which *DeepSeek-R1* assigns a 100% relevance score. All results are robust to using the full set of keywords from the *Pollution and Waste* dictionary. We thank the authors of Lin et al. (2024) for generously sharing their code used to measure the dictionary-based proxies of environmental and social disclosures.

[15] Specifically, we use the Chinese Broker and Financial Analysts System (CBAS) database accessed via CNRDS. Prior studies often rely on the CSMAR database for financial analyst forecasts and characteristics. We use CNRDS because it offers the most comprehensive coverage of financial analysts in China.

[16] If multiple analysts are listed, we use the phone number of the lead analyst, identified as the first-listed analyst on the report.

program's implementation, we restrict the sample to analyst–firm pairs with at least one report both before and after the program's adoption. We further limit the sample to periods up to 2013Q4, the final adoption quarter, as no untreated analysts remain to serve as valid controls thereafter. These filters yield a final sample of 39,950 analyst reports issued by 715 unique analysts covering 1,460 unique firms. Table 1 presents the distribution of analyst reports across cities in our sample. Finally, we construct a stacked cohort–report–level dataset as described in Section 4.1, resulting in a final sample of 67,389 report-cohort observations.

We obtain firm-level emissions data from the Environmental Survey and Reporting (ESR) database, stock returns from the CSMAR database, news coverage of air pollution from the China National Knowledge Infrastructure (CNKI), and internet search activity from the Baidu Index platform. Table 3 reports summary statistics for the key variables used in our analyses. On average, 2.7% of analyst reports discuss air pollution, as identified using the SASB-based definition (*Air Pollution Discussed*). The mean market reaction to an analyst report is 0.82%, with the interquartile range spanning from –1.9% (first quartile) to 3.1% (third quartile). These magnitudes indicate that analyst reports convey economically meaningful information to investors and significantly influence perceptions of firm value.

In terms of firm characteristics, 10.9% and 10.6% of the observations in our sample are associated with firms categorized as "green" and "brown," respectively, based on classifications obtained using the LLM *DeepSeek-Reasoner* applied to firms' 2011 MD&A business descriptions. In addition, 18.1% of the observations correspond to firms classified as brown using the government-designated classification and thus included within the monitoring scope of China's Ministry of Environmental Protection in 2011.

5. Results

5.1. Effect of the monitoring program on analyst discussions of air pollution

Table 4, Panel A presents the results from estimating Equation 2 with *Air Pollution Discussed* as the dependent variable. We find that the coefficient on *Treated* × *Post* is positive and statistically significant at the 1% level (coef. = 0.022). This result indicates that, following

the implementation of the monitoring program in the analyst's city, treated analysts are more likely to discuss air pollution in their reports on the firms they cover, relative to control analysts covering the same firm in the same period. The estimated coefficient implies that treated analysts are 2.2 percentage points more likely to discuss pollution, representing an increase of approximately 105% relative to the pre-treatment mean of *Air Pollution Discussed*.

Figure 3 plots the event-time differences in mentions of air pollution in treated and control analysts' reports in the four quarters leading up to treatment, and two subsequent quarters. Specifically, we replace the *Post* variable in Equation 2 with a series of quarter-since-program indicators ($Pre[\leq 4]$, $Pre[3]$, $Pre[2]$, $Pre[1]$, $Post[1]$, and $Post[\geq 2]$, using the event quarter as the baseline. We find no evidence of differential pre-treatment trends in *Air Pollution Discussed*, followed by a sharp and persistent increase in treated analysts' discussions of air-polluting activities after treatment.

Next, to mitigate concerns that the rollout of the monitoring program is confounded by broader increases in awareness of nonfinancial factors and their relation to firm value, we conduct two placebo tests using analysts' discussions of social topics in their reports. If the monitoring program specifically increases the salience of air pollution, rather than heightening attention to nonfinancial issues more generally, we should observe no differential change in treated analysts' discussions of social topics (unrelated to pollution).

We test this prediction by estimating Equation 2, replacing the dependent variable with two proxies for analyst discussions of social topics based on categories developed by the SASB. The SASB classifies social topics into two broad categories: Human Capital and Social Capital. We instruct DeepSeek-R1 to construct two indicator variables capturing whether an analyst report explicitly discusses human capital or social capital, as defined by the SASB. Table 4, Panel B, shows that there is no statistically significant change in mentions of social issues in the reports of treated analysts. In fact, the estimated coefficients are economically close to zero and statistically indistinguishable from zero, despite pre-treatment mean discussion rates of approximately 10% for human capital and 8% for social capital.

To further explore, we descriptively examine how treated analysts frame their pollution-related discussions by classifying them into four types of environmental risks. The first category captures the physical effects of climate change or pollution on a firm's operations or assets (e.g., damage to facilities from extreme weather events). The second captures regulatory risks, including costs imposed by, or opportunities arising from, environmental policies and regulation (e.g., higher costs due to carbon taxes or emission caps, or opportunities to help other firms comply with regulatory requirements). The third captures changes in consumer preferences and demand driven by pollution or climate concerns (e.g., reduced demand for pollution-intensive products or increased demand for products that mitigate pollution-related health risks, such as air filters or masks). Throughout, we use the term "risk" broadly to denote firms' exposure to pollution- and climate-related factors that may entail both adverse consequences (e.g., higher costs, regulatory constraints, reduced market share) and favorable consequences (e.g., new markets, competitive advantages, policy support). Finally, we include an "Other Risks" category for discussions of air pollution that cannot reasonably be assigned to any of the three primary categories.

We use DeepSeek-R1 to classify analyst discussions of air pollution based solely on the text of analyst reports. A report may be assigned to more than one category. We operationalize these constructs by creating four indicator variables: *Physical Risks Discussed*, *Regulatory Risks Discussed*, *Preference-related Factors Discussed*, and *Other Risks Discussed*, each equal to one if the report discusses air pollution within the respective category. Reports that contain no discussion of air pollution are coded as zero for all four indicators.

Examples of pollution-related discussions corresponding to each category are provided in Internet Appendix D. Most reports that discuss air pollution are classified as addressing regulatory risks and/or preference-related factors: 77% of such reports fall into the regulatory risk category and 70% into the preference-related category, while each of the remaining categories accounts for less than 10% of pollution-related discussions.

Table 5 presents the results from estimating Equation 2 with each of the four indicator

variables as the dependent variable. We find that the rollout of the pollution monitoring program is associated with approximately a two-fold increase in discussions of regulatory risks and preference-related factors, while the estimated effects for the remaining two categories are economically small and statistically insignificant. In particular, Columns 2 and 3 show that treated analysts are 1.7 and 1.3 percentage points more likely to discuss regulatory risks and preference-related factors, respectively, corresponding to increases of approximately 94% and 81% relative to the pre-program means of these outcomes.

Taken together, these findings suggest that the monitoring program, by heightening the salience of local air pollution, leads analysts to devote greater attention to the implication of pollution and climate change for the firms they cover. Notably, treated analysts' discussions concentrate on regulatory and preference-related channels rather than on physical risks, suggesting that heightened pollution salience primarily shifts attention toward mechanisms that may affect firms' near-term cash flows.

5.2. Heterogeneous effects by firms' exposure to environmental risk

We next examine whether the effect of the monitoring program varies with cross-sectional differences in firms' exposure to climate change and transition risks. Different firms may be differentially affected by environmental risks, creating winners and losers. For example, firms in pollution-intensive industries, such as coal, are likely to be adversely affected by the realization of transition risks, whereas firms in cleaner industries, such as renewable energy, may benefit. To capture this heterogeneity, we employ two complementary approaches to classify firms based on their exposure to environmental risks.

Our first approach uses a large language model (LLM) to classify firms into three groups: brown firms that are expected to incur net costs from environmental risks, green firms that are expected to benefit from such risks, and neutral firms for which the net effect is ambiguous. Specifically, we instruct *DeepSeek-Reasoner* to classify firms as brown or green based on business descriptions in the MD&A sections of their annual reports, guided by the SASB definition of air quality. Firms that are neither classified as green nor brown are designated as neutral. Using

this procedure, we classify 149 firms as brown (*Brown Firm–LLM classification*), 184 as green (*Green Firm–LLM classification*), and the remaining 1,127 firms as neutral (*Neutral Firm–LLM classification*).[17]

Our second approach identifies firms negatively exposed to environmental risks using the Environmental Survey and Reporting (ESR) database, a proprietary firm-level dataset administered by China's Ministry of Environmental Protection (MEP).[18] The ESR is the most comprehensive environmental database in China, covering major pollution-emitting establishments and requiring detailed reporting of emissions of key pollutants, including chemical oxygen demand (COD) and sulfur dioxide (SO_2). The data are collected through a hybrid system in which firms self-report their emissions to local Environmental Protection Bureaus, with submissions subject to random verification by government auditors; moreover, the individual responsible for reporting is legally accountable for the accuracy of the information. To further ensure data quality for policy-making purposes, the Environmental Protection Law stipulates that ESR data cannot be directly used as the basis for penalizing or regulating firms, thereby reducing incentives for strategic misreporting (He et al., 2020).

The ESR dataset covers the largest polluters: within each county-year, pollution-emitting establishments are ranked by their emissions, and firms jointly accounting for approximately 85% of total emissions are included in the database (He et al., 2020). As a result, the ESR provides a near-complete coverage of major emitters and serves as the primary data source for studying environmental regulation in China.[19] We define *Brown Firm–Govt classification* as firms listed in the ESR dataset in the year preceding the monitoring program, as the inclusion indicates they are among the largest emitters in their counties. In our sample, 353 firms are classified as brown under this definition, while 1,107 firms are not.

Table 6, Panels A and B, report the results from estimating Equation 2 separately for

[17] Internet Appendix C provides additional details on the performance of *DeepSeek-Reasoner*, including a validation exercise in which two research assistants independently classify firms as green or brown and compare their classifications to those of the LLM.

[18] The MEP was reorganized and renamed the Ministry of Ecology and Environment in 2018.

[19] This dataset is not suitable for measuring real-time local pollution exposure, as firm-level emissions data are released with a substantial lag—typically several years after collection—and are not available in real time.

analyst reports covering *Brown*, *Green*, and *Neutral* firms based on the LLM classification, and *Brown* and *Not Brown* firms based on inclusion in the ESR database (henceforth, government classification). Panel A shows that mentions of air pollution in treated analysts' report increase by 6.1 percentage points for green firms and 5.0 percentage points for brown firms, relative to control analysts covering the same firms in the same period. In economic terms, these estimates correspond to increases of approximately 73% and 185%, respectively, relative to the pre-treatment means. Bn contrast, mentions of air pollution for neutral firms increase by only 1.3 percentage points post-treatment, and this increase is significantly smaller than that for green and brown firms.

Panel B presents analogous evidence using the government classification. We find that, following treatment, treated analysts are approximately four times more likely to discuss air pollution in reports on *Brown* firms relative to the corresponding change for control analysts covering the same firms. By contrast, for *Not Brown* firms (i.e., firms not included in the ESR database), the increase in pollution-related discussion is approximately 50% and is significantly smaller than that for brown firms.

Taken together, the evidence in Panels A and B indicates that the rollout of the monitoring program leads analysts located in treated cities to increase their discussion of air pollution disproportionately for firms that are more exposed to environmental risks. We interpret these results as consistent with pollution monitoring increasing the salience of environmental risk for treated analysts.

In additional analyses reported in the Internet Appendix, we build on our findings in Section 5.1 that analysts primarily increase discussions of transition risks (i.e., risks related to changes in regulation and consumer preferences). Columns 1–3 of Panels A and B in Table B3 shows that discussions of regulatory risks and preference-related factors increase significantly among treated analysts covering *Brown* and *Green* firms, whereas we find no significant change for *Neutral* firms. Similarly, using the government-based classification, Columns 4 and 5 in the table show that the increase in discussions of these risk types is significantly stronger for analysts

covering *Brown* firms relative to those covering *Not Brown* firms. Overall, these results indicate that analysts' discussions of air-polluting activities—and, in particular, regulatory and demand-driven environmental risks—are concentrated among firms for which such risks are most likely to be financially material.

5.3. Effect of the monitoring program on analyst quantitative outputs

Our analyses thus far show that the monitoring program leads analysts to discuss firms' exposure to pollution-related risks more extensively. We next examine whether these changes in narrative content translate into revisions in valuation as reflected in their quantitative outputs, including earnings forecasts, stock recommendations, target prices, and report tone. In particular, we predict that analysts adjust their valuation assessments in response to the monitoring program, with the direction and magnitude of these adjustments depending on firms' exposure to environmental risks. Firms with high emissions (brown firms) are likely to face higher regulatory risks and lower demand, while environmentally friendly (green) firms are likely to experience new growth opportunities and enhanced demand. We predict that the heightened salience of pollution motivates treated analysts to assign greater weight to information about brown firms' higher regulatory risks and potential demand reductions, leading them to issue more pessimistic earnings forecasts, lower target prices, and less favorable stock recommendations. In contrast, we predict that increased salience can increase the weight analysts place on information about new growth opportunities and enhanced demand, leading to more favorable analyst outputs for green firms. By comparison, we expect little change for environmentally neutral firms, for which pollution-related risks are less likely to be financially material.

To test our predictions, we estimate Equation 2 using analyst outputs as the dependent variable. Specifically, we examine four measures: (i) *EPS Forecast*, defined as the analyst's forecast of annual earnings per share (EPS) scaled by the firm's stock price at the beginning of the year (multiplied by 100); (ii) *Recommendation*, an ordinal variable ranging from 1 to 5, with higher values indicating more favorable recommendations; (iii) *Target Price*, defined as the ratio

of the analyst's target price forecast to the firm's stock price at the beginning of the fiscal year; and (iv) *Report Tone*, defined as the difference between the number of positive and negative words in an analyst report, scaled by the total number of positive and negative words.

Table 7 presents the results. In Panel A, we find that the quantitative outputs of treated analysts is not significantly different than that of the control analysts for the average firm in our sample. However, once we partition firms based on their exposure to environmental risks, the results are striking. Panel B reports results using the LLM-based classification. We find that treated analysts issue more favorable reports for green firms and less favorable reports for brown firms, relative to the control analysts covering the same firms in the same period.

For green firms, column 1 shows that treated analysts *EPS Forecast* is, on average, 6.4% higher than that of control analysts. Similarly, columns 4, 7 and 10 show that treated analysts' *Recommendation*, *Target Price* forecast, and *Report Tone* are 3.5%, 11.4%, and 28.4% higher, respectively.[20] In contrast, the effects for brown firm are of the opposite sign. Columns 3, 6, 9 and 12 show that treated analysts' *EPS Forecast*, *Recommendation*, *Target Price* forecast, and *Report Tone* are 7.8%, 3.8%, 9.9%, and 22.3% lower, respectively, than that of control analysts (for the same firm in the same period). For environmentally neutral firms, we find no statistically significant differences between treated and control analysts, and the estimated effects are economically small.

Panel C presents analogous results using the government-designated classification. Following the implementation of the monitoring program, treated analysts issue lower EPS forecasts, less favorable stock recommendations, lower target prices, and more negative tone relative to control analysts covering the same *Brown* firms. The estimated effects correspond to approximately 2.9%, 2.9%, and 12.2%, of the pre-program mean values of *EPS Forecast*, *Recommendation*, and *Target Price*, respectively; and 15.2%, of the pre-program standard deviation of *Report Tone*.

[20] We measure economic magnitudes by comparing the coefficient estimate for *Treated* × *Post* with the pre-program mean value of the dependent variables for *EPS Forecast*, *Recommendation*, and *Target Price*. However, since the value of *Report Tone* can be both positive and negative, when the dependent variable is *Report Tone*, we measure economic significance by comparing the coefficient estimate for *Treated* × *Post* with the pre-program standard deviation of *Report Tone*.

In contrast, we find no significant differences for between treated and control analyst reports for *Not Brown* firms, and the differences between the two groups are statistically significant across all measures. Collectively, these results indicate that the monitoring program affects analysts' valuation judgments in a manner consistent with the financial materiality of environmental risks.

To provide insight into the mechanism underlying the changes in analysts' outputs, we examine whether treated analysts increase their information acquisition efforts in response to heightened pollution salience. Corporate site visits provide a natural proxy for such efforts. Prior research shows that site visits allow analysts to gather soft information about firms' operations, engage directly with management, and better assess firm-specific risks that are difficult to infer from public disclosures (e.g., Cheng et al., 2016; Chen et al., 2022).[21] Insofar as increased salience of pollution and climate change leads analysts to more actively evaluate firms' environmental exposure, we would expect treated analysts to allocate more effort toward collecting information on firms for which such risks are most likely to be financially material, namely, green and brown firms.

To test this prediction, we construct a firm-year-quarter-analyst level sample and estimate a specification analogous to Equation 2 with an indicator variable equal to one if the analyst visits the covered firm during the quarter (*Site Visit*) as the dependent variable. Table 8 presents the results. Consistent with our prediction, treated analysts significantly increase site visits to both green and brown firms following the implementation of the monitoring program, while we observe no corresponding increase for environmentally neutral firms. In economic terms, site visits by treated analysts increase by approximately 307% for green firms and 153% for brown firms relative to their pre-program means. We find similar results when partitioning firms using the government-designated classification. These results suggest that heightened pollution salience not only affects how analysts interpret available information but also induces them to acquire additional firm-specific information, particularly for firms whose valuations are more sensitive

[21] In China, listed firms are required to publicly disclose records of investor relations activities, including analyst or institutional investor site visits. These disclosures include the date of the visit and identity of the visiting analyst or institution. We obtain these data from the CNRDS database.

to environmental risks.

5.4. Stock market reaction to analyst reports

We next examine whether the changes in analyst outputs documented above translate into changes in the stock prices of the firms they cover. On the one hand, if heightened pollution salience leads treated analysts to more accurately incorporate financially material environmental risks into their valuations, stock prices should adjust in the direction implied by these revisions. On the other hand, if increased salience causes analysts to overweight environmental risks relative to their true economic importance, their reports may reflect overly pessimistic assessments for brown firms and overly optimistic assessments for green firms, in which case stock price reactions may be muted (or any initial price reaction may subsequently reverse).

We measure market reaction as the signed cumulative abnormal return over the three-day window centered on the analyst report date (*Market Reaction*) and estimate Equation 2 using this measure as the dependent variable. Table 9 presents the results. In the full sample, we find no significant average change in market reactions to reports issued by treated analysts relative to control analysts (see column 1). The full sample result is consistent with result in Table 7, Panel A, which shows that quantitative outputs of treated analysts is not significantly different than that of the control analysts for the average firm in our sample.

However, market reactions vary systematically with firms' exposure to environmental risks, consistent with our earlier findings in Panels B and C of Table 7. For brown firms, investors react more negatively to reports issued by treated analysts relative to control analysts covering the same firms in the same period. In contrast, for green firms, we observe more positive market reactions to reports issued by treated analysts. We find no significant differences for environmentally neutral firms. In economic terms, the release of a report by a treated analyst is associated with a 0.86% market reaction for green firms and a -1.15% market reaction for brown firms. These effects are economically large, corresponding to 18.3% and 25.3% of the standard deviation of *Market Reaction*, respectively.[22] We find similar results using the government-

[22] As noted earlier, we use the standard deviation rather than the mean to assess the economic magnitude of *Market Reaction*, as this variable can take negative values and has a mean close to zero. Scaling treatment effects

designated classification. Specifically, *Brown* firms experience a -1.37% market reaction following reports issued by treated analysts in the post-treatment, whereas the market reaction for *Not Brown* firms is 0.08% and statistically indistinguishable from zero. Overall, these results suggest that the monitoring program influences market prices by increasing the salience of environmental risks to financial analysts, particularly when such risks are financially material.

5.5. Stock return reversal and price efficiency

We next examine whether the stock price reactions documented above reflect investors' rational incorporation of environmental risk or an overreaction to salient pollution information. Prior research shows that investors tend to overweight salient information, which can lead to temporary price distortions and subsequent return reversals (e.g., Afrouzi, Kwon, Landier, Ma, and Thesmar, 2023; deHaan, Lee, and Loh, 2025). If heightened pollution salience induces analysts and investors to overreact to environmental risks, the initial price response to analyst reports should reverse over longer horizons. Accordingly, we examine whether the initial market reaction to analyst reports is associated with subsequent long-run returns.

Specifically, we estimate a modified version Equation 2 using the post-report buy-and-hold abnormal returns over a 12-month horizon as the dependent variable.[23] Further, we include additional interaction terms between *Treat*, *Post*, and *Market Reaction* (i.e., the initial market reaction to the release of the analyst report). A negative relation between the initial market reaction and subsequent returns would indicate reversal and, hence, initial overreaction. We examine whether this relation is more negative for reports issued by treated analysts than for those issued by control analysts, i.e., whether reversal is stronger for reports issued by treated analysts.

Table 10 presents the results. Across all specifications—including the full sample and subsamples based on firms' environmental risk exposure—we find no evidence of a change in return reversal. In particular, the relation between initial market reactions and subsequent

by the mean would therefore yield unstable and difficult-to-interpret magnitudes.

[23]We use a 12-month post-report horizon to allow for the disclosure of subsequent earnings announcements, which would help correct any initial overreaction. However, Table B4 in the Internet Appendix shows our inferences are robust to using a one-month horizon.

returns is not significantly different for reports issued by treated analysts relative to control analysts. These findings suggest that the price reactions documented in Section 5.4 do not reflect temporary sentiment or overreaction, but instead capture investors' rational updating of firms' exposure to environmental risks.

To corroborate the above inference, we examine whether the monitoring program improves price efficiency. If analyst reports more effectively incorporate the economic impact of environmental risk into prices following the program, less new information should be revealed at subsequent earnings announcements, leading to weaker market reactions around those announcements (Chen et al., 2022). To test this prediction, we construct a firm-level measure of exposure to treated analysts based on the proportion of analysts covering the firm who are located in cities that have adopted the monitoring program. Specifically, for each firm-year-quarter, we measure *Treated Analyst Ratio* as the proportion of treated analysts to the total number of analysts covering the firm at the beginning of the quarter. We then examine whether firms with a higher *Treated Analyst Ratio* experience smaller earnings-announcement returns. We measure *Market Reaction to Earnings Announcement* as the absolute value of the cumulative abnormal return over a three-day window centered on the quarterly earnings announcement date.

Table 11 reports the results. We find that a higher share of treated analysts is associated with significantly lower market reactions to earnings announcements for both green and brown firms, with no corresponding effect for neutral firms. In economic terms, a one-standard-deviation increase in the ratio of treated analysts covering a firm reduces its earnings-announcement news by approximately 16–17% relative to its pre-program mean for green and brown firms. Similar patterns emerge using the government-based classification.[24]

[24]Table B5 in the Internet Appendix examines the profitability of stock recommendations, measured following Chen et al. (2022). This proxy measures the net abnormal return from taking a long position following recommendation upgrades and a short position following recommendation downgrades. The table shows that the profitability of recommendations issued by treated analysts increases for green and brown firms relative to neutral firms. These results indicate that stock recommendations become more informative about future returns and contain more value-relevant information, providing further support for our argument that analyst recommendations contain more information relevant to the pricing of environmental risk after the program.

Collectively, these findings indicate that the monitoring program improves the incorporation of environmental risk into stock prices. The absence of return reversals suggests that market reactions reflect rational updating rather than behavioral overreaction, while the decline in earnings-announcement responses indicates that relevant information is incorporated into prices more quickly. Overall, the evidence is consistent with enhanced price efficiency following the increase in pollution salience.[25]

5.6. Additional and robustness tests

We conduct several additional analyses, tabulated in the Internet Appendix, to assess the robustness of our findings and to further address potential alternative explanations. First, we implement an alternative identification strategy that does not rely on the staggered timing of the monitoring program. Specifically, we focus on Chinese firms that are cross-listed in foreign markets and compare changes in reports issued by analysts residing in mainland China to those issued by analysts located outside mainland China (e.g., in the U.S. or Hong Kong) who cover the same firms at the same time. Because foreign analysts are not directly exposed to local pollution conditions in China, this design isolates variation in exposure to pollution salience while holding firm-level information constant.[26] The results, reported in B6, Panels A-F, and Figure B1, are consistent with those from our baseline specification, providing additional support for our inference.

Second, we examine several cross-sectional tests that further shed light on the mechanism. Table B7 reports these results. In columns 1 and 2, we find that the effects of the monitoring

[25] A potential alternative explanation is that the monitoring program improves analysts' cognitive functioning rather than affecting their perceptions of environmental risk. Prior research shows that exposure to air pollution impairs cognitive performance, while reduced exposure improves decision-making (e.g., Li et al., 2020; Dong et al., 2021). In our setting, increased salience of pollution may lead treated analysts to adopt defensive behaviors (e.g., reducing outdoor exposure, use of masks), thereby improving their cognitive abilities and, in turn, their valuation accuracy. However, this explanation is inconsistent with our findings. If improved cognition were the primary mechanism, we would expect treated analysts to outperform control analysts across all firms. Instead, we find no improvement in the valuation of environmentally neutral (or *Not Brown*) firms, suggesting that the observed effects are driven by changes in the salience and weighting of environmental risks rather than by general improvements in cognitive functioning.

[26] As noted earlier, we recognize that geographic proximity may confer an information advantage to analysts based in mainland China relative to those located in the U.S. or Hong Kong. Our identification, however, relies on changes in analysts' behavior around the rollout of the monitoring program. As long as any such information advantage is time-invariant (e.g., analysts do not relocate to another city), it is absorbed by our fixed effects and does not affect our inferences.

program are weaker for analysts located in cities with a U.S. embassy or consulate, where pollution information was more readily accessible prior to the program. The U.S. Embassy in Beijing, and later in U.S. Consulates in other cities, began reporting hourly $PM_{2.5}$ levels on their Twitter accounts to inform U.S. citizens traveling to China. Although Twitter was—and remains—inaccessible in China, constraining access to pollution information prior to the monitoring program, analysts residing in these cities may have had relatively greater access to pollution information through alternative channels. Thus, the rollout of the monitoring program potentially provided less incremental information in these locations. Consistent with this intuition, we predict and find that the effect of the monitoring program on analysts' discussions of air pollution is weaker for treated analysts residing in cities with a U.S. Embassy or Consulate than for those in cities without one.

Survey evidence suggests that younger individuals are more likely to express concern about environmental issues, seek information on such topics, support environmentally friendly policies, and engage in both individual and collective actions—such as lifestyle changes and climate activism—to address environmental risks (e.g., Tyson, Kennedy, and Funk, 2021; Poortinga, Demski, and Steentjes, 2023). Consistent with this evidence, we predict and find that the effects of the monitoring program are stronger for reports issued by younger analysts (columns 3 and 4). And last, we find that the effects of the monitoring program are stronger for higher-quality (star) analysts, who are better able to incorporate new information into their valuation assessments (columns 5 and 6). Overall, these findings are consistent with the interpretation that the monitoring program operates by increasing the salience of pollution information and that analysts who are more attentive to or better able to process such information respond more strongly.

Third, we verify that our results are robust to alternative measures and specifications. In particular, our findings remain unchanged when using an alternative dictionary-based measure of pollution-related discussion following Lin et al. (2024). In particular, Lin et al. (2024) employs a word embedding model to create a dictionary for quantifying pollution disclosure.

Table B8 shows that are inferences are unchanged using this approach. We also employ alternative specifications for our heterogeneity analyses. In particular, rather than estimating separate regressions for green, brown, and neutral firms, we estimate a single regression with triple interaction terms for firms with different exposures to environmental risks. Table B9 shows that our inferences are unchanged.

Fourth, we examine the sensitivity of our results to alternative sample restrictions. Our findings are robust to excluding reports issued by analysts located in the same city as the covered firm (Table B10), limiting the sample to firms that are not treated during the sample period (i.e., firms in cities that adopt the monitoring program after 2013Q3; Table B11), and sequentially excluding individual treatment cohorts (Table B12). In addition, our results are robust to alternative clustering approaches (Table B13) and to including additional controls for analyst experience and the length of the analyst–firm relationship (Table B14).

Finally, we confirm that our results are robust to using an alternative design – staggered DiD specification – that compares treated analysts to both earlier- and later-treated analysts, rather than relying solely on not-yet-treated analysts as controls. The results from this specification are consistent with those from our main design (see Table B15). Overall, these additional analyses reinforce our main conclusion that the observed changes in analyst behavior and market outcomes are driven by increased salience of pollution information rather than by confounding factors or model specification choices.

6. Conclusion

This paper examines whether ambient environmental monitoring influences how financially sophisticated market participants, namely financial analysts, incorporate environmental risk into firm valuations. We study the staggered rollout of China's nationwide air quality monitoring program, which substantially increased the salience of local air pollution without differentially altering analysts' access to firm-specific information. Exploiting variation in the timing of monitoring across cities and the geographic dispersion of analysts covering the same firm at the same time, we isolate the effect of heightened pollution salience – holding firm

fundamentals and information sets constant – on analysts' attention, valuation judgments, and the stock market's response to their reports.

We document three primary findings. First, when pollution monitoring is introduced in an analyst's city of residence, the analyst becomes significantly more likely to discuss air pollution in research reports, relative to other analysts covering the same firm in the same quarter but residing in not-yet-treated cities. This increase is economically large, more than doubling the pre-treatment baseline frequency of pollution-related discussion, and is not accompanied by an increase in discussions of unrelated nonfinancial topics, such as human or social capital. Content analyses reveal that treated analysts' pollution-related discussions concentrate on regulatory risks and changes in consumer demand rather than on physical climate risks, suggesting that heightened pollution salience shifts attention toward channels that affect firms' near-term cash flows.

Second, we show that heightened pollution salience translates into changes in analysts' quantitative outputs when environmental risks are likely to be financially material. Treated analysts issue more pessimistic earnings forecasts, lower target prices, less favorable stock recommendations, and more negative report tone for high-emission ("brown") firms, while issuing more favorable outputs for environmentally beneficial ("green") firms. In contrast, we find no meaningful changes in outputs for environmentally neutral firms. Moreover, treated analysts increase corporate site visits for brown and green firms, consistent with heightened information acquisition when pollution risk becomes more salient.

Third, we show that these changes in analyst outputs are transmitted to prices. Stock prices respond negatively to reports on brown firms and positively to reports on green firms when the reports are issued by treated analysts in the post-monitoring period. Importantly, these announcement-window price reactions do not subsequently reverse, and the information content of future earnings announcements declines as the share of treated analysts covering a firm increases. Together, these findings suggest that pollution monitoring improves the incorporation of environmental risk into stock prices, enhancing price efficiency rather than

generating temporary sentiment-driven overreaction.

Our results contribute to several strands of the literature. First, we add to research on environmental conditions and financial markets. Prior studies document that exposure to pollution or extreme weather can impair cognitive functioning and distort financial decision-making. In contrast, we show that ambient environmental monitoring—holding pollution levels and weather conditions constant—can improve decision-making by increasing the salience of financially relevant environmental risks. Thus, while adverse environmental shocks may generate biases, policy-driven increases in salience can enhance the processing of risk-relevant information.

Second, we contribute to the literature on salience and economic behavior. Much of the existing evidence emphasizes that salient shocks, such as natural disasters, lead to overweighting of risk and potential mispricing. Our setting differs in that the salience shock arises from an information policy rather than an extreme realization of environmental conditions, and we find little evidence of overreaction or reversal. Instead, heightened salience appears to correct underweighting of environmental risk, particularly for firms where such risk is financially material. These findings suggest that salience can operate not only as a source of bias but also as a mechanism through which markets more accurately incorporate latent risks.

Third, we contribute to the literature on environmental disclosure and the pricing of environmental risk. Rather than examining the release of new firm-specific environmental disclosures, we hold the firm-level information environment constant and exploit variation in the salience of publicly available pollution information. Our evidence shows that even when the underlying information set does not change differentially across market participants, shifts in attention can alter how that information is weighted in valuation. In this sense, ambient environmental monitoring serves as a complement to firm-level disclosure by influencing how existing information is processed.

Our findings have implications for the design of environmental policy. The monitoring program we study was not primarily intended to affect capital markets; it was designed to

improve transparency and public awareness of pollution. Yet our results indicate that such monitoring can have meaningful spillover effects on financial markets by increasing the salience of environmental risks for key information intermediaries. In doing so, monitoring can shape capital allocation by raising the cost of capital for highly polluting firms and lowering it for environmentally beneficial firms. These effects occur without mandating changes in emissions or directly altering firms' disclosure obligations. Thus, environmental monitoring can function as a low-cost policy lever that operates through attention and belief updating.

References

Afrouzi, Hassan, Spencer Y Kwon, Augustin Landier, Yueran Ma, and David Thesmar, 2023, Overreaction in expectations: Evidence and theory, *The Quarterly Journal of Economics* 138, 1713–1764.

Alok, Shashwat, Nitin Kumar, and Russ Wermers, 2020, Do fund managers misestimate climatic disaster risk, *The Review of Financial Studies* 33, 1146–1183.

Anderson, Michael L, Minwoo Hyun, and Jaecheol Lee, 2022, Bounds, benefits, and bad air: Welfare impacts of pollution alerts, *Working Paper* .

Bae, Kee-Hong, René M Stulz, and Hongping Tan, 2008, Do local analysts know more? a cross-country study of the performance of local analysts and foreign analysts, *Journal of financial economics* 88, 581–606.

Baker, Andrew C., David F. Larcker, and Charles C. Wang, 2022, How much should we trust staggered difference-in-differences estimates?, *Journal of Financial Economics* 144, 370–395.

Barwick, Panle Jia, Shanjun Li, Liguo Lin, and Eric Y. Zou, 2024, From fog to smog: The value of pollution information, *American Economic Review* 114, 1338–1381.

Bolton, Patrick, and Marcin Kacperczyk, 2021, Do investors care about carbon risk?, *Journal of Financial Economics* 142, 517–549.

Bolton, Patrick, and Marcin Kacperczyk, 2023, Global pricing of carbon-transition risk, *The Journal of Finance* 78, 3677–3720.

Bordalo, Pedro, Nicola Gennaioli, and Andrei Shleifer, 2013, Salience and asset prices, *American Economic Review* 103, 623–28.

Bordalo, Pedro, Nicola Gennaioli, and Andrei Shleifer, 2022, Salience, *Annual Review of Economics* 14, 521–544.

Branigan, Tania, 2015, Beijing authorities sanguine as pollution documentary takes china by storm, https://www.theguardian.com/world/2015/mar/05/beijing-sanguine-pollution-documentary-china, The Guardian.

Cakici, Nusret, and Adam Zaremba, 2022, Salience theory and the cross-section of stock returns: International and further evidence, *Journal of Financial Economics* 146, 689–725.

Chang, Tom Y, Wei Huang, and Yongxiang Wang, 2018, Something in the air: Pollution and the demand for health insurance, *The Review of Economic Studies* 85, 1609–1634.

Chen, Deqiu, Yujing Ma, Xiumin Martin, and Roni Michaely, 2022, On the fast track: Information acquisition costs and information production, *Journal of Financial Economics* 143, 794–823.

Chen, Jiafeng, and Jonathan Roth, 2024, Logs with zeros? some problems and solutions, *The Quarterly Journal of Economics* 139, 891–936.

Chen, Yi-Chun, Mingyi Hung, and Yongxiang Wang, 2018, The effect of mandatory csr disclosure on firm profitability and social externalities: Evidence from china, *Journal of accounting and economics* 65, 169–190.

Cheng, Qiang, Fei Du, Xin Wang, and Yutao Wang, 2016, Seeing is believing: Analysts' corporate site visits, *Review of Accounting Studies* 21, 1245–1286.

Choi, Darwin, Zhenyu Gao, and Wenxi Jiang, 2020, Attention to global warming, *The Review of Financial Studies* 33, 1112–1145.

Cohn, Jonathan B., Zack Liu, and Malcolm I. Wardlaw, 2022, Count (and count-like) data in finance, *Journal of Financial Economics* 146, 529–551.

Cosemans, Mathijs, and Rik Frehen, 2021, Salience theory and stock prices: Empirical evidence, *Journal of Financial Economics* 140, 460–483.

De Chaisemartin, Clément, and Xavier d'Haultfoeuille, 2020, Two-way fixed effects estimators with heterogeneous treatment effects, *American economic review* 110, 2964–2996.

deHaan, Ed, Charles MC Lee, and Wei Ting Loh, 2025, Local-thinking bias, *The Accounting Review* 100, 87–112.

deHaan, Ed, Joshua Madsen, and Joseph D. Piotroski, 2017, Do weather-induced moods affect the processing of earnings news?, *Journal of Accounting Research* 55, 509–550.

Dell, Melissa, Benjamin F Jones, and Benjamin A Olken, 2012, Temperature shocks and economic growth: Evidence from the last half century, *American Economic Journal: Macroeconomics* 4, 66–95.

Derrien, François, Philipp Krueger, Augustin Landier, and Tianhao Yao, 2025, Esg news, future cash flows, and firm value, *The Journal of Finance* 80, 3499–3554.

Dessaint, Olivier, and Adrien Matray, 2017, Do managers overreact to salient risks? Evidence from hurricane strikes, *Journal of Financial Economics* 126, 97–121.

Dong, Rui, Raymond Fisman, Yongxiang Wang, and Nianhang Xu, 2021, Air pollution, affect, and forecasting bias: Evidence from Chinese financial analysts, *Journal of Financial Economics* 139, 971–984.

Downar, Benedikt, Jürgen Ernstberger, Stefan Reichelstein, Sebastian Schwenen, and Aleksandar Zaklan, 2021, The impact of carbon disclosure mandates on emissions and financial operating performance, *Review of Accounting Studies* 26, 1137–1175.

Fisman, Raymond, Pulak Ghosh, Arkodipta Sarkar, and Jian Zhang, 2026, Dirty air and green investments: The impact of pollution information on portfolio allocations, *Journal of Financial Economics* Forthcoming.

Giglio, Stefano, Bryan Kelly, and Johannes Stroebel, 2021, Climate finance, *Annual Review of Financial Economics* 13, 15–36.

Greenstone, Michael, Guojun He, Ruixue Jia, and Tong Liu, 2022, Can technology solve the principal-agent problem? Evidence from China's war on air pollution, *American Economic Review: Insights* 4, 54–70.

Greenstone, Michael, Guojun He, Shanjun Li, and Eric Yongchen Zou, 2021, China's war on pollution: Evidence from the first 5 years, *Review of Environmental Economics and Policy* .

He, Guojun, Shaoda Wang, and Bing Zhang, 2020, Watering down environmental regulation in China*, *The Quarterly Journal of Economics* 135, 2135–2185.

Huang, Jiekun, Nianhang Xu, and Honghai Yu, 2020, Pollution and performance: Do investors make worse trades on hazy days?, *Management Science* .

Ilhan, Emirhan, Philipp Krueger, Zacharias Sautner, and Laura T Starks, 2023, Climate risk disclosure and institutional investors, *The Review of Financial Studies* 36, 2617–2650.

Kuehn, Bridget M, 2014, Who: More than 7 million air pollution deaths each year, *Jama* 311, 1486–1486.

Li, Chao Kevin, Jin-hui Luo, and Naomi S. Soderstrom, 2020, Air pollution and analyst information production, *Journal of Corporate Finance* 60, 101536.

Li, Jennifer (Jie), Massimo Massa, Hong Zhang, and Jian Zhang, 2021, Air pollution, behavioral bias, and the disposition effect in China, *Journal of Financial Economics* 142, 641–673.

Lin, Yan, Rui Shen, Jasmine Wang, and Y. Julia Yu, 2024, Global evolution of environmental and social disclosure in annual reports, *Journal of Accounting Research* 62, 1941–1983.

Loughran, Tim, and Bill McDonald, 2011, When is a liability not a liability? textual analysis, dictionaries, and 10-ks, *The Journal of finance* 66, 35–65.

Lubos, Pastor, Robert F. Stambaugh, and Lucian A. Taylor, 2022, Dissecting green returns, *Journal of Financial Economics* 146, 403–424.

Petersen, Mitchell A, 2008, Estimating standard errors in finance panel data sets: Comparing approaches, *The Review of financial studies* 22, 435–480.

Poortinga, Wouter, Christina Demski, and Katharine Steentjes, 2023, Generational differences in climate-related beliefs, risk perceptions and emotions in the UK, *Communications Earth & Environment* 4, 229.

Shao, Heng, 2015, Only in china: why a smog documentary sends chinese stocks soaring to trading limit, https://www.forbes.com/sites/hengshao/2015/03/02/only-in-china-why-a-smog-documentary-sends-chinese-stocks-soaring-beyond-trading-limit/, Forbes Asia.

Starks, Laura T, 2023, Presidential address: Sustainable finance and esg issues—value versus values, *The Journal of Finance* 78, 1837–1872.

Tomar, Sorab, 2023, Greenhouse gas disclosure and emissions benchmarking, *Journal of Accounting Research* 61.

Tyson, Alec, Brian Kennedy, and Cary Funk, 2021, Gen Z, millennials stand out for climate change activism, social media engagement with issue: Majorities of Americans support array of measures to address climate change but stop short of full break with fossil fuels, Technical report, Pew Research Center.

Xie, Tingting, Ye Yuan, and Hui Zhang, 2023, Information, awareness, and mental health: Evidence from air pollution disclosure in China, *Journal of Environmental Economics and Management* 120, 102827.

Zhang, Shaojun, 2025, Carbon returns across the globe, *The Journal of Finance* 80, 615–660.

Appendix A. Variables Definitions

Variable	Definition	Data Source
Awareness of Air Pollution Tests [Table 2]		
News Coverage	This is a city-quarter–level measure defined as the number of news articles containing air pollution–related keywords, including "smog" or "air pollution," in the title and referencing the city's name in the text of the article, regardless of where the newspaper is published or distributed. The data include articles from both national newspapers (including *People's Daily*) and local newspapers (including *Beijing Daily*).	China National Knowledge Infrastructure
Internet Search	The average daily frequency of internet searches for air pollution-related keywords, including "smog" or "air pollution" within a given city and quarter. The daily search frequencies are obtained from Baidu, China's most widely used search engine.	Baidu Index platform
Treated City	An indicator variable that equals one for treated cities in each cohort and zero for control cities in the cohort.	The program's rollout dates were manually collected from news media and city yearbooks
Post	An indicator variable that equals one for both treated and control cities in the cohort starting in the first quarter when the city implements the monitoring program and remains one for all subsequent quarters.	The program's rollout dates were manually collected from news media and city yearbooks
Main Variables		
Treated	An indicator variable that equals one for treated analysts in each treatment cohort and zero for control analysts in the cohort. In each adoption quarter (i.e., treatment cohort), treated analysts are those residing in cities that adopt the program in that quarter, and control analysts are those in cities that adopt the program in subsequent quarters.	The program's rollout dates were manually collected from news media and city yearbooks
Post	An indicator variable that equals one for both treated and control analysts starting in the first quarter when the treated analyst's city implements the monitoring program and remains one for all subsequent quarters. The implementation quarter is defined as the quarter in which the rollout date allows for at least one and a half months of coverage. For example, if the rollout date is in the earlier part of a quarter, *Post* equals one starting in that quarter. However, if the rollout date is late in the quarter (providing less than one and a half months of coverage), *Post* equals one starting in the following quarter.	The program's rollout dates were manually collected from news media and city yearbooks

Air Pollution Discussed [Panel A of Table 4]		
Air Pollution Discussed	An indicator variable that equals one if the analyst's report discusses air quality. This variable is derived by instructing a generative large language model (*DeepSeek-R1*) to focus exclusively on the content of analyst reports and classify whether they discuss air quality issues as defined by the Sustainability Accounting Standards Board (SASB).	CnOpenData & *DeepSeek-R1*
Placebo Variables [Panel B of Table 4]		
Human Capital Discussed	An indicator variable that equals one if the analyst's report discusses human capital. This variable is derived by instructing a generative large language model (*DeepSeek-R1*) to focus exclusively on the content of analyst reports and classify whether they discuss human capital issues as defined by the Sustainability Accounting Standards Board (SASB).	CnOpenData & *DeepSeek-R1*
Social Capital Discussed	An indicator variable that equals one if the analyst's report discusses social capital. This variable is derived by instructing a generative large language model (*DeepSeek-R1*) to focus exclusively on the content of analyst reports and classify whether they discuss social capital issues as defined by the Sustainability Accounting Standards Board (SASB).	CnOpenData & *DeepSeek-R1*
Different Types of Environmental Risks [Table 5]		
Physical Risks Discussed	An indicator variable that equals one if the analyst's report discusses physical risks arising from climate change or pollution (e.g., damage to the firm's assets from extreme weather events). We use *DeepSeek-R1* to classify these discussions based solely on the text of the analyst reports, instructing the model to interpret "risk" broadly as the firm's exposure to factors that may entail adverse consequences (e.g., damage to assets, disruptions to operations) or positive consequences (e.g., increased demand for the firm's products that help customers manage physical risks).	CnOpenData & *DeepSeek-R1*
Regulatory Risks Discussed	An indicator variable that equals one if the analyst's report discusses regulatory risks arising from environmental policies (e.g., carbon pricing, caps on total emissions or energy use). We use *DeepSeek-R1* to classify these discussions based solely on the text of the analyst reports, instructing the model to interpret "risk" broadly as the firm's exposure to factors that may entail adverse consequences (e.g., higher costs due to carbon taxes, environmental penalties) or positive consequences (e.g., government environmental subsidies).	CnOpenData & *DeepSeek-R1*

Preference-related Factors Discussed	An indicator variable that equals one if the analyst's report discusses changes in customer demand or competitive dynamics driven by concerns about pollution or climate change. We use *DeepSeek-R1* to classify these discussions based solely on the text of the analyst reports, instructing the model to interpret "risk" broadly as the firm's exposure to factors that may entail adverse consequences (e.g., reduced demand for the firm's pollution-intensive products) or positive consequences (e.g., increased demand for the firm's products that help customers mitigate the negative health consequences of pollution, such as air filters or masks).	CnOpenData & *DeepSeek-R1*
Other Risks Discussed	An indicator variable that equals one if the analyst's report discusses air pollution but the discussion cannot reasonably be classified into any other category. We use *DeepSeek-R1* to classify these discussions based solely on the text of the analyst reports, instructing the model to classify a report into this category if the analyst discusses air pollution but *DeepSeek-R1* does not assign the discussion to any of *Physical Risks*, *Regulatory Risks*, or *Preference-related Factors*.	CnOpenData & *DeepSeek-R1*
Heterogeneity Variables [Table 6]		
Green Firm–LLM classification	An indicator variable that equals one if the firm is a green firm. This variable is derived by instructing a generative large language model (*DeepSeek-Reasoner*) to focus exclusively on the firm's business description in the MD&A section of the annual reports of 2011 and to classify the firm as green if the description indicates that the firm gains an advantage or opportunity from heightened attention to, concern about, and regulation of air quality issues, as defined by the Sustainability Accounting Standards Board (SASB).	Annual reports & *DeepSeek-Reasoner*
Brown Firm–LLM classification	An indicator variable that equals one if the firm is a brown firm. This variable is derived by instructing a generative large language model (*DeepSeek-Reasoner*) to focus exclusively on the firm's business description in the MD&A section of the annual reports of 2011 and to classify the firm as brown if the description indicates that the firm faces costs or risks arising from heightened attention to, concern about, and regulation of air quality issues, as defined by the Sustainability Accounting Standards Board (SASB).	Annual reports & *DeepSeek-Reasoner*
Neutral Firm–LLM classification	An indicator variable that equals one if the firm is neither a *Green Firm–LLM classification* nor a *Brown Firm–LLM classification*.	Annual reports & *DeepSeek-Reasoner*

Brown Firm–Govt classification	An indicator variable that equals one if a firm is identified as the primary source of pollution and consequently included within the monitoring scope of China's Ministry of Environmental Protection in 2011. In each county and year, polluting establishments are ranked by their emissions of chemical oxygen demand (COD) and sulfur dioxide (SO_2), and those jointly accounting for about 85% of total emissions are included in the ESR database (He et al., 2020). This inclusion results in the availability of pollutant emission data in the Environmental Survey and Reporting (ESR) database.	ESR
Not Brown Firm–Govt classification	An indicator variable that equals one if a firm is not *Brown Firm–Govt classification*.	ESR
Analyst Outputs [Tables 7]		
EPS Forecast (%)	The analyst's earnings per share (EPS) forecast, scaled by the firm's stock price at the beginning of the fiscal year (multiplied by 100).	CNRDS & CSMAR
Recommendation	The analyst's stock recommendation is coded as an ordinal variable ranging from 1 to 5, where 5 indicates a strong buy and 1 indicates a strong sell.	CNRDS
Target Price	The ratio of the analyst's target price forecast to the firm's actual stock price at the beginning of the fiscal year.	CnOpenData & CSMAR
Report Tone	*ReportTone* is calculated as $(Positive - Negative)/(Positive + Negative)$, where $Negative$ ($Positive$) represents the word count frequency of negative (positive) words in the text of the analyst report. Negative and positive words are identified using the Loughran-McDonald dictionary (Loughran and McDonald, 2011).	CnOpenData
Site Visits [Table 8]		
Site Visit	An indicator variable that equals one if the lead analyst or any of their team members visits the covered firm during the quarter, zero otherwise. The data on analysts' corporate site visits to firms are available for firms listed on the Shenzhen Stock Exchange (SZSE).	CNRDS
Market Reaction [Tables 9]		
Market Reaction (%)	The (signed) cumulative abnormal return over a three-day window centered on the analyst report date, multiplied by 100. Daily abnormal returns are measured as the firm's stock return minus the equally-weighted market return. We exclude analyst reports issued on firms' annual earnings announcement dates to avoid capturing market reactions driven by earnings announcements rather than analyst reports.	CSMAR

Return Reversal [Tables 10]		
Post-Analyst-Report BHAR (%)	Measured as the signed buy-and-hold abnormal return (BHAR) of the covered firm over the window starting from the second trading day after the analyst report date and ending 12 months after the analyst report date, multiplied by 100. BHAR is calculated as: $$\text{BHAR}_{i,t_2,T} = \prod_{\tau=t_2}^{T}(1+R_{i,\tau}) - \prod_{\tau=t_2}^{T}(1+E[R_{i,\tau}])$$ where $R_{i,\tau}$ is the daily stock return of firm i on day τ, $E[R_{i,\tau}]$ is the equally-weighted market return on day τ, t_2 is the second trading day after the analyst report date, and T is the last trading day of the 12-calendar month after the analyst report date. We exclude analyst reports issued on firms' annual earnings announcement dates to avoid capturing market reactions driven by earnings announcements rather than analyst reports.	CSMAR
Stock Price Efficiency [Tables 11]		
Market Reaction to Earnings Announcement (%)	The absolute value of the cumulative abnormal return over a three-day window centered on the quarterly earnings announcement date, multiplied by 100. Daily abnormal returns are measured as the firm's stock return minus the equally-weighted market return.	CSMAR
Treated Analyst Ratio	The proportion of treated analysts covering the firm divided by the total number of analysts covering the firm, measured at the beginning of the quarter. We standardize this measure to have a mean of zero and a standard deviation of one.	CNRDS

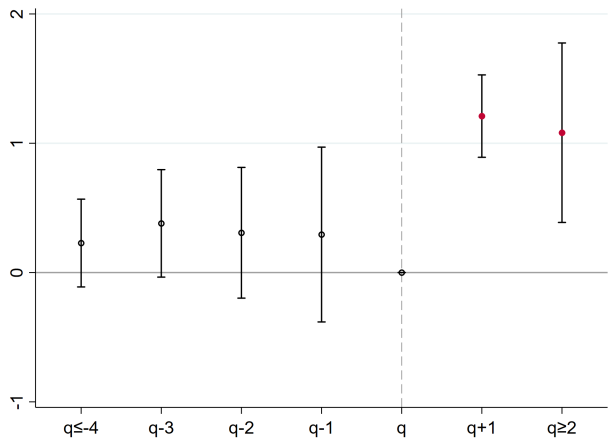
Figure 1. Effect of the monitoring program on public access to air quality information

The model estimated using Poisson regressions:

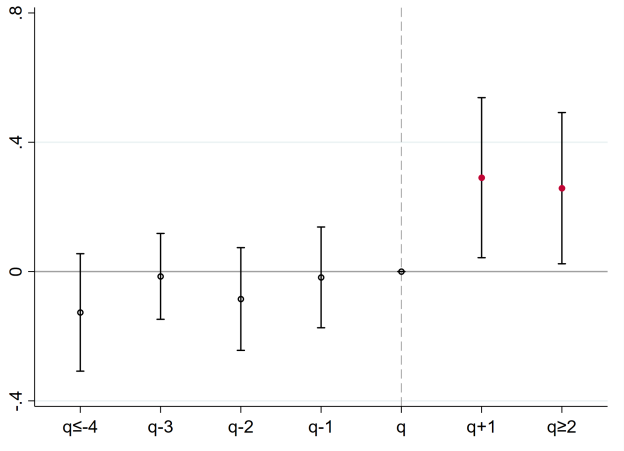
$$y_{city,q,c} = \beta_1 \, Treated \; City_{city,c} \times PRE + \beta_2 \, Treated \; City_{city,c} \times POST + \alpha_{city,c} + \alpha_{q,c} + \varepsilon_{city,q,c}$$

where, *city*, q, and c index cities, calendar year-quarters, and treatment cohorts, respectively. PRE is a vector that includes $Pre[\leq 4]_{q,c}$, $Pre[3]_{q,c}$, $Pre[2]_{q,c}$, and $Pre[1]_{q,c}$; and $POST$ is a vector that includes $Post[1]_{q,c}$ and $Post[\geq 2]_{q,c}$.

Panel A: ***News Coverage***



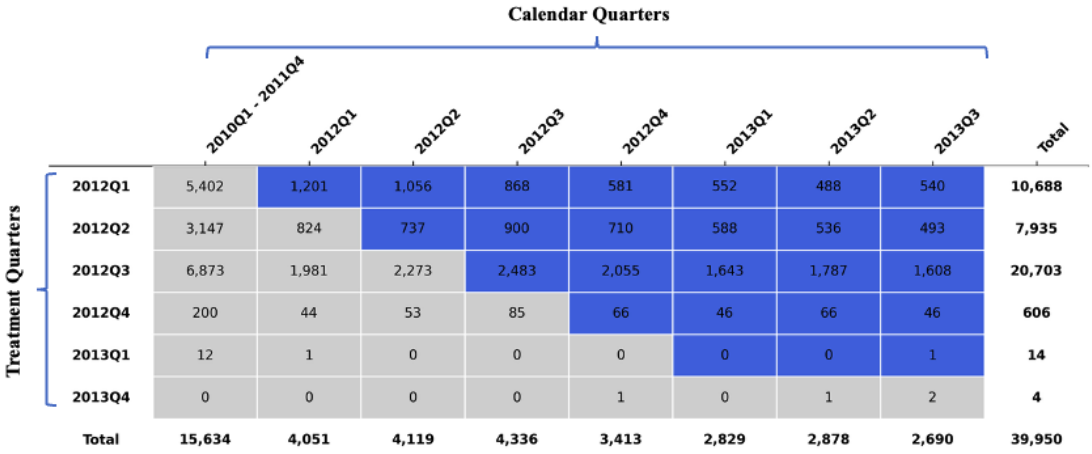
Panel B: ***Internet Search***



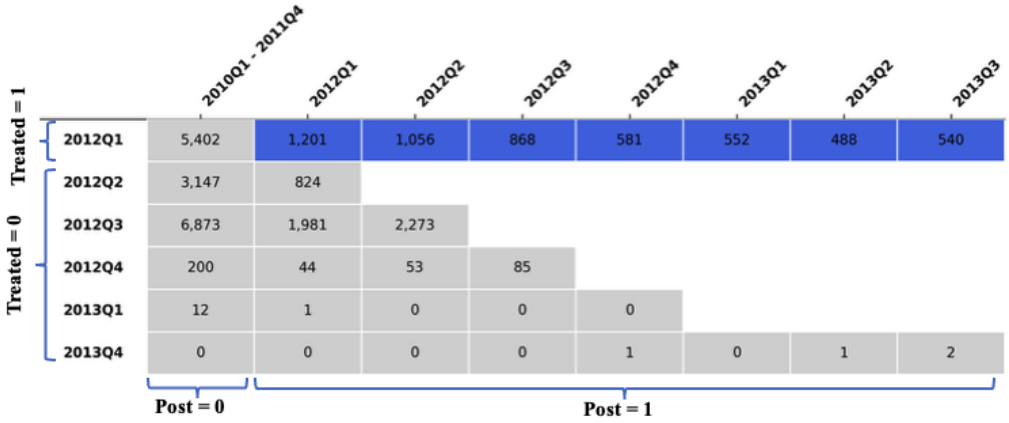
Notes: This figure presents evidence of the effect of the monitoring program on the awareness about air pollution for quarters before and after the monitoring program's implementation. The estimated coefficients are obtained from estimating Equation 1 modified by replacing *Post* with a set of indicator variables for quarters before and after the program's implementation (except implementation quarter q, which is the base quarter). In Panel A, we use *News Coverage*, defined as the number of news articles containing air pollution-related keywords, including "smog" or "air pollution," in the title and a reference to the city in the text during the quarter. In Panel B, we use *Internet Search*, defined as the average daily frequency of internet searches on the Baidu platform for air pollution-related keywords, including "smog" or "air pollution" within a given city and quarter. Both panels are estimated using Poisson regressions. Vertical lines represent the 90% confidence intervals for each parameter estimate using standard errors clustered at the City × Year level. Each shaded (unshaded) triangle on the graph represents a significant (insignificant) regression coefficient.

Figure 2. Stacked cohort DiD design: Treated analyst reports vs. not-yet-treated analyst reports

Panel A: Distribution of analyst reports across quarters in the final sample



Panel B: Cohort 1 (2012Q1 vs 2012Q2-2013Q4)



Panel C: Cohort 2 (2012Q2 vs 2012Q3-2013Q4)

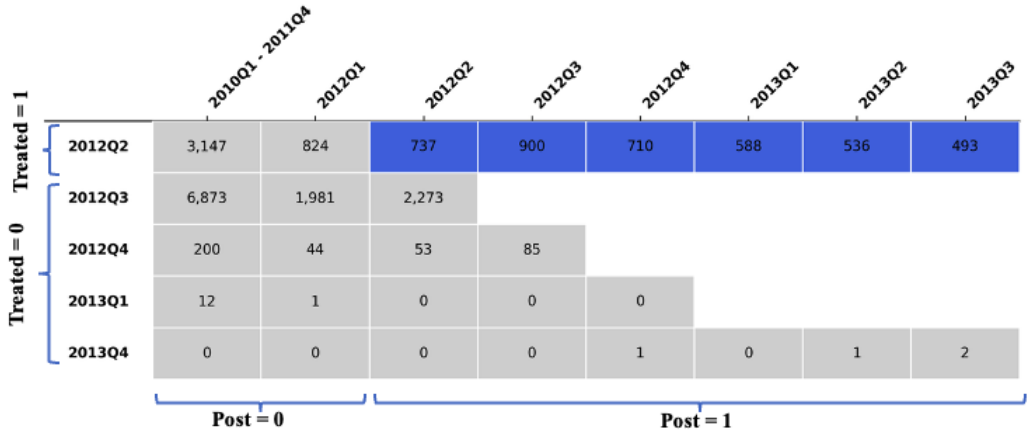


Figure 2 (Continued)

Notes: Panel A reports the total number of analyst reports by treatment quarter and calendar quarter, with each cell showing the number for that treatment quarter and calendar quarter. Each row corresponds to one treatment quarter, and each column represents a calendar quarter. For example, treatment quarter 2012Q1 includes all analyst reports issued by analysts in cities that adopted the monitoring program in 2012Q1, the first adoption quarter. Blue cells denote quarters in which the corresponding calendar quarter is treated, while gray cells represent pre-treatment quarters. Cities in the last treatment quarter are treated in 2013Q4. However, we do not use analyst reports from that treatment quarter as treated observations in our stacked cohort DiD design because no later-treated analyst reports remain to serve as controls.

Panels B and C illustrate the number of analyst reports across treatment quarters and calendar quarters for two of the five cohorts used in our stacked DiD design. Panel B presents Cohort 1, where reports issued by analysts in cities implementing the program in 2012Q1 form the treated group, and reports from analysts in other cities serve as controls until their own adoption.

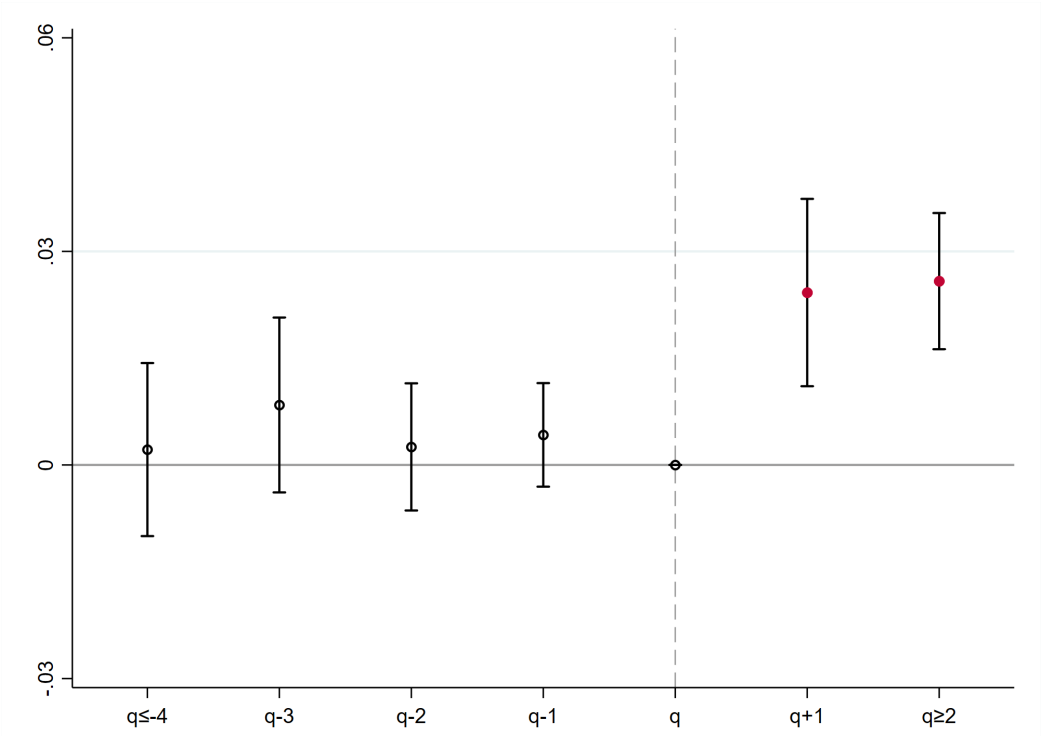
Panel C presents Cohort 2, where reports issued by analysts in cities that implemented the program in 2012Q2 serve as the treated group and reports from analysts in cities that implemented the program after 2012Q2 serve as controls. To ensure valid comparisons, control observations are restricted to not-yet-treated reports; therefore, analysts treated in 2012Q1 are excluded from Cohort 2. Our main sample includes five such cohorts, which we stack into a single dataset for analysis.

Figure 3. *Air Pollution Discussed* before and after the program's implementation

The model estimated:

$$y_{i,j,q,c} = \beta_1 \, Treated_{i,c} \times PRE + \beta_2 \, Treated_{i,c} \times POST + \alpha_{j,q,c} + \alpha_{i,j,c} + \varepsilon_{i,j,q,c}$$

where, i, j, q, and c index analysts, firms, calendar year-quarters, and treatment cohorts, respectively. PRE is a vector that includes $Pre[\leq 4]_{q,c}$, $Pre[3]_{q,c}$, $Pre[2]_{q,c}$, and $Pre[1]_{q,c}$; and $POST$ is a vector that includes $Post[1]_{q,c}$ and $Post[\geq 2]_{q,c}$.



Notes: This figure presents proxies of analyst discussions of firms' air-polluting activities before and after the monitoring program's implementation. The estimated coefficients are obtained from estimating Equation 2 modified by replacing *Post* with a set of indicator variables for quarters before and after the program's implementation (except implementation quarter q, which is the base quarter). *Air Pollution Discussed* is an indicator variable that equals one if the analyst's report discusses air quality. Vertical lines represent the 90% confidence intervals for each parameter estimate using standard errors clustered at the City × Year level. Each shaded (unshaded) triangle on the graph represents a significant (insignificant) regression coefficient.

Table 1. The distribution of analyst reports across cities

		First quarter in which we set *Post* equal to one						
City	**Rollout date**	**2012Q1**	**2012Q2**	**2012Q3**	**2012Q4**	**2013Q1**	**2013Q4**	**Total**
Beijing	21-Jan-2012	10,688						**10,688**
Dongguan	8-Mar-2012		127					**127**
Guangzhou	8-Mar-2012		2,399					**2,399**
Shenzhen	8-Mar-2012		2,632					**2,632**
Hangzhou	25-Mar-2012		994					**994**
Suzhou	27-Mar-2012		9					**9**
Changzhou	30-Mar-2012		18					**18**
Wuxi	30-Mar-2012		259					**259**
Nanjing	30-Mar-2012		1,493					**1,493**
Tianjin	30-Apr-2012		4					**4**
Taiyuan	5-Jun-2012			34				**34**
Shanghai	27-Jun-2012			20,669				**20,669**
Fuzhou	31-Oct-2012				173			**173**
Wuhan	2-Nov-2012				433			**433**
Changsha	2-Dec-2012					12		**12**
Dalian	28-Dec-2012					2		**2**
Guilin	30-Oct-2013						4	**4**
Total		**10,688**	**7,935**	**20,703**	**606**	**14**	**4**	**39,950**

Notes: This table reports the rollout dates for cities in our sample ("Rollout date"), the number of analyst reports for analysts residing in each city over our sample period, and the first quarter in which we set the indicator variable *Post* equal to one ("implementation quarter"). We define the implementation quarter based on the program's rollout date, requiring at least one and a half months of coverage for *Post* to equal one in that quarter. Accordingly, if the rollout occurs in the first half of a quarter, *Post* is set to one beginning in that quarter; if it occurs in the second half, *Post* is coded as one starting in the following quarter.

Table 2. Effect of the monitoring program on public access and awareness of air quality information

The model estimated using Poisson regressions:

$$y_{city,q,c} = \beta \; Treated \; City_{city,c} \times Post_{q,c} + \alpha_{city,c} + \alpha_{q,c} + \varepsilon_{city,q,c}$$

where, *city*, *q*, and *c* index cities, calendar year-quarters, and treatment cohorts, respectively.

$y \Rightarrow$	(1) *News Coverage*	(2) *Internet Search*
Treated City × *Post*	0.954***	0.318**
	(0.221)	(0.099)
Observations (City-Year-Quarter-Cohort level)	568	406
Number of Unique Cities	17	17
City × Cohort FE	Yes	Yes
Year-Quarter × Cohort FE	Yes	Yes
Pseudo R^2	83.6%	75.8%
Marginal Effect	160%	37%

Notes: This table reports evidence of the effect of the monitoring program on the awareness about air pollution using a stacked cohort DiD design. The program is implemented across Chinese cities in six quarters (six treatment quarters) over a span of eight quarters, from the first quarter of 2012 to the fourth quarter of 2013. For each adoption quarter, we define treated cities as those adopting the program in that quarter, and use cities that adopt the program in later quarters as the control group. For example, cities that adopt the program in 2012Q1 (treatment quarter 1) are designated as treated cities in Cohort 1, while later-adopting cities (treatment quarters 2 through 6) serve as controls for that cohort until their own adoption. We do not use cities from treatment quarter 6 as treated observations because no later-treated cities remain to serve as controls. The final sample includes five cohorts stacked into a single dataset. *Treated City* is an indicator variable that equals one for treated cities in each cohort and zero for control cities in the cohort. *Post* is an indicator variable that equals one for both treated and control cities in the cohort starting in the first quarter when the city implements the monitoring program and remains one for all subsequent quarters. We measure awareness using two proxies. *News Coverage* is defined as the number of news articles containing air pollution-related keywords, including "smog" or "air pollution," in the title and a reference to the city in the text during the quarter and *Internet Search* is defined as the average daily frequency of internet searches on Baidu for air pollution-related keywords, including "smog" or "air pollution" within a given city and quarter. Both columns are estimated using Poisson regressions. All variables are defined in the Variable Appendix. Standard errors are clustered at the City × Year level and reported in parentheses. *, **, *** indicate statistical significance at the 10%, 5%, and 1% levels (two-sided), respectively.

Table 3. Summary Statistics

Variable	N	Mean	SD	Q1	Median	Q3
Main Variables						
Treated	67,389	0.593	0.491	0.000	1.000	1.000
Post	67,389	0.398	0.490	0.000	0.000	1.000
Air Pollution Discussed	67,389	0.027	0.161	0.000	0.000	0.000
Physical Risks Discussed	67,389	0.001	0.034	0.000	0.000	0.000
Regulatory Risks Discussed	67,389	0.021	0.142	0.000	0.000	0.000
Preference-related Factors Discussed	67,389	0.019	0.135	0.000	0.000	0.000
Other Risks Discussed	67,389	0.002	0.048	0.000	0.000	0.000
EPS Forecast (%)	67,071	5.138	3.349	2.844	4.305	6.407
Recommendation	65,389	4.329	0.595	4.000	4.000	5.000
Target Price	21,705	1.290	0.620	0.996	1.240	1.448
Report Tone	67,389	−0.011	0.289	−0.222	−0.014	0.200
Site Visit	63,747	0.039	0.193	0.000	0.000	0.000
Market Reaction (%)	56,688	0.865	4.621	−1.960	0.366	3.162
Post-Analyst-Report BHAR(%)	56,688	−3.057	34.168	−25.508	−7.973	12.847
Market Reaction to Earnings Announcement(%)	12,287	3.325	3.102	1.096	2.444	4.559
Treated Analyst Ratio (standardized)	12,287	0.000	1.000	−0.972	−0.453	1.104
Placebo Tests						
Human Capital Discussed	67,389	0.096	0.295	0.000	0.000	0.000
Social Capital Discussed	67,389	0.081	0.272	0.000	0.000	0.000
Heterogeneity Tests						
Green Firm–LLM classification	67,389	0.109	0.312	0.000	0.000	0.000
Neutral Firm–LLM classification	67,389	0.785	0.411	0.000	0.000	0.000
Brown Firm–LLM classification	67,389	0.106	0.308	0.000	0.000	0.000
Not Brown Firm–Govt classification	67,389	0.819	0.385	1.000	1.000	1.000
Brown Firm–Govt classification	67,389	0.181	0.385	0.000	0.000	0.000
Awareness of Air Pollution Tests						
News Coverage	568	4.063	21.659	0.000	1.000	3.000
Internet Search	406	61.190	58.110	27.000	44.000	72.000

Notes: This table reports summary statistics for variables used in our analyses. *Treated* is an indicator variable that equals one for treated analysts in each cohort and zero for control analysts in the cohort. *Post* is an indicator variable that equals one for both treated and control analysts in the cohort starting in the first quarter when the treated analyst's city implements the monitoring program and remains one for all subsequent quarters. *Air Pollution Discussed* is an indicator variable that equals one if the analyst's report discusses air quality as defined by the SASB and measured using a large language model (*DeepSeek-R1*). *EPS Forecast* is defined as the analyst's EPS forecast, scaled by the firm's stock price at the beginning of the fiscal year, multiplied by 100. *Recommendation* is the analyst's stock recommendation, coded as an ordinal variable ranging from 1 to 5, where 5 indicates a Strong Buy and 1 indicates a Strong Sell. *Target Price* is the ratio of the analyst's target price forecast to the firm's actual stock price at the beginning of the fiscal year. *Report Tone* is calculated as (Positive - Negative) / (Positive + Negative), where Negative (Positive) represents the word count frequency of negative (positive) words in the analyst report as obtained from the CNRDS dataset. Negative and positive words are identified using the Loughran-McDonald dictionary. *Market Reaction (%)* is the (signed) cumulative abnormal return over a three-day window centered on the analyst report date, multiplied by 100. All continuous variables are winsorized at the 1% and 99% levels. All variables are defined in the Variable Appendix.

Table 4. Main analyses

The model estimated:

$$y_{i,j,q,c} = \beta\ Treated_{i,c} \times Post_{q,c} + \alpha_{j,q,c} + \alpha_{i,j,c} + \varepsilon_{i,j,q,c}$$

where, i, j, q, and c index analysts, firms, calendar year-quarters, and treatment cohorts, respectively.

Panel A. Effect of monitoring program on analyst discussions of firms' air-polluting activities

$y \Rightarrow$	(1) *Air Pollution Discussed*
Treated × *Post*	0.022***
	(0.005)
Observations (Analyst Report-Cohort Level)	67,389
Number of Unique Analysts	715
Number of Unique Firms	1,460
Firm × Year-Quarter × Cohort FE	Yes
Analyst × Firm × Cohort FE	Yes
Adj. R^2	47.4%
Pre-program Mean of y	0.021
Pre-program Standard Deviation of y	0.145

Panel B. Placebo tests using analyst discussions of social topics

$y \Rightarrow$	(1) *Human Capital Discussed*	(2) *Social Capital Discussed*
Treated × *Post*	0.011	0.003
	(0.012)	(0.008)
Observations (Analyst Report-Cohort Level)	67,389	67,389
Number of Unique Analysts	715	715
Number of Unique Firms	1,460	1,460
Firm × Year-Quarter × Cohort FE	Yes	Yes
Analyst × Firm × Cohort FE	Yes	Yes
Adj. R^2	16.5%	35.5%
Pre-program Mean of y	0.096	0.079
Pre-program Standard Deviation of y	0.294	0.270

Table 4 (Continued)

Notes: This table reports results on the effect of the monitoring program on analyst discussions of firms' activities in their reports. Panel A reports evidence on the effects of a monitoring program implemented in China on analyst discussions of firms' air-polluting activities in their reports using a stacked cohort DiD design. The program is implemented across Chinese cities in six quarters (six treatment quarters) over a span of eight quarters, from the first quarter of 2012 to the fourth quarter of 2013. For each adoption quarter, treated analysts are defined as those in cities adopting the program in that quarter, and analysts in cities that adopt the program in later quarters are used as the control group. For example, analysts in cities that adopt the program in 2012Q1 (treatment quarter 1) are designated as treated analysts in Cohort 1, while analysts in later-adopting cities (treatment quarters 2 through 6) serve as controls for that cohort until their own adoption. We do not use analysts located in cities in treatment quarter 6 as treated observations because no later-treated analysts remain to serve as controls. The final sample includes five cohorts stacked into a single dataset. *Air Pollution Discussed* is an indicator variable that equals one if the analyst's report discusses air quality as defined by the SASB and measured using a large language model (*DeepSeek-R1*). Panel B reports results of placebo tests using social topics as placebo topics. Specifically, this panel reports evidence on the effects of the monitoring program on analyst discussions of social topics in their reports using a stacked cohort DiD design. The dependent variable in Column 1 (Column 2) is *Human Capital Discussed* (*Social Capital Discussed*), defined as an indicator variable that equals one if the analyst's report discusses human capital (social capital) as defined by the SASB and measured using a large language model (*DeepSeek-R1*). In both panels, *Treated* is an indicator variable that equals one for treated analysts in each cohort and zero for control analysts in the cohort. *Post* is an indicator variable that equals one for both treated and control analysts in the cohort starting in the first quarter when the treated analyst's city implements the monitoring program and remains one for all subsequent quarters. All variables are defined in the Variable Appendix. Standard errors are clustered at the City × Year level and reported in parentheses. *, **, *** indicate statistical significance at the 10%, 5%, and 1% levels (two-sided), respectively.

Table 5. Analyst discussions of different types of environmental risks

The model estimated:

$$y_{i,j,q,c} = \beta \, Treated_{i,c} \times Post_{q,c} + \alpha_{j,q,c} + \alpha_{i,j,c} + \varepsilon_{i,j,q,c}$$

where, i, j, q, and c index analysts, firms, calendar year-quarters, and treatment cohorts, respectively.

$y \Rightarrow$	(1) *Physical Risks Discussed*	(2) *Regulatory Risks Discussed*	(3) *Preference-related Factors Discussed*	(4) *Other Risks Discussed*
Treated × *Post*	0.000	0.017***	0.013***	0.001
	(0.000)	(0.005)	(0.003)	(0.002)
Observations (Analyst Report-Cohort Level)	67,389	67,389	67,389	67,389
Number of Unique Analysts	715	715	715	715
Number of Unique Firms	1,460	1,460	1,460	1,460
Firm × Year-Quarter × Cohort FE	Yes	Yes	Yes	Yes
Analyst × Firm × Cohort FE	Yes	Yes	Yes	Yes
Adj. R^2	23.5%	42.5%	46.2%	26.0%
Pre-program Mean of y	0.001	0.018	0.016	0.002
Pre-program Standard Deviation of y	0.031	0.133	0.124	0.047

Notes: This table reports the effects of the monitoring program on analyst discussions of different types of environmental risks. In Column 1, the dependent variable *Physical Risk Discussed* equals one if the analyst discusses physical risks arising from climate change or air pollution. In Column 2, *Regulatory Risks Discussed* equals one if the analyst discusses environmental regulatory risks. In Column 3, *Preference-related Factors Discussed* equals one if the analyst discusses changes in customer preference and demand driven by pollution or climate concerns. In Column 4, *Other Risks Discussed* equals one if the analyst discusses air pollution in the report but the discussion cannot reasonably be classified into any of the three preceding categories. We use *DeepSeek-R1* to classify these discussions based solely on the text of the analyst reports, instructing the model to interpret "risk" broadly as the firm's exposure to pollution- or climate-related factors—such as past, current, or anticipated regulation, physical conditions, or shifts in customer preferences—that may entail adverse consequences (e.g., higher costs, constraints, reduced market share) or positive consequences (e.g., new markets, competitive advantages, cost savings, policy support). *Treated* is an indicator variable that equals one for treated analysts in each cohort and zero for control analysts in the cohort. *Post* is an indicator variable that equals one for both treated and control analysts in the cohort starting in the first quarter when the treated analyst's city implements the monitoring program and remains one for all subsequent quarters. All variables are defined in the Variable Appendix. Standard errors are clustered at the City × Year level and reported in parentheses. *, **, *** indicate statistical significance at the 10%, 5%, and 1% levels (two-sided), respectively.

Table 6. Heterogeneity tests

The model estimated:

$$y_{i,j,q,c} = \beta \, Treated_{i,c} \times Post_{q,c} + \alpha_{j,q,c} + \alpha_{i,j,c} + \varepsilon_{i,j,q,c}$$

where, i, j, q, and c index analysts, firms, calendar year-quarters, and treatment cohorts, respectively.

Panel A. LLM-based classification

	(1)	(2)	(3)
$y \Rightarrow$		*Air Pollution Discussed*	
LLM-based classification $\Rightarrow$	*Green*	*Neutral*	*Brown*
Treated × *Post*	0.061**	0.013***	0.050***
	(0.023)	(0.002)	(0.018)
p-value for $\beta_{Green} - \beta_{Neutral} > 0$		0.010	
p-value for $\beta_{Brown} - \beta_{Neutral} > 0$		0.015	
p-value for $\beta_{Green} - \beta_{Brown} > 0$		0.349	
Observations (Analyst Report-Cohort Level)	7,353	52,876	7,160
Number of Unique Analysts	292	684	257
Number of Unique Firms	184	1,127	149
Firm × Year-Quarter × Cohort FE	Yes	Yes	Yes
Analyst × Firm × Cohort FE	Yes	Yes	Yes
Adj. R^2	45.4%	44.7%	39.2%
Pre-program Mean of y	0.083	0.012	0.027
Pre-program Standard Deviation of y	0.276	0.110	0.162

Panel B. Government-designated classification

	(1)	(2)
$y \Rightarrow$	*Air Pollution Discussed*	
Government-designated classification $\Rightarrow$	*Not Brown*	*Brown*
Treated × *Post*	0.011***	0.084***
	(0.003)	(0.031)
p-value for $\beta_{Brown} - \beta_{Not\ Brown} > 0$	0.008	
Observations (Analyst Report-Cohort Level)	55,182	12,207
Number of Unique Analysts	690	462
Number of Unique Firms	1,107	353
Firm × Year-Quarter × Cohort FE	Yes	Yes
Analyst × Firm × Cohort FE	Yes	Yes
Adj. R^2	44.8%	50.9%
Pre-program Mean of y	0.022	0.020
Pre-program Standard Deviation of y	0.146	0.139

Table 6 (Continued)

Notes: This table reports results on the heterogeneity of the effect of the monitoring program on analyst discussions of firms' air-polluting activities in their reports. In Panel A, we partition analyst reports into three groups: *Brown*, *Neutral*, and *Green*. We instruct *DeepSeek-Reasoner* to focus exclusively on the firm's business description in the MD&A section of the annual reports of 2011 and to classify a firm as *Brown* (*Green*) if its business description indicates that the firm faces risks or costs (gains an advantage or opportunity) from heightened attention to, concern about, and regulation of air quality issues, as defined by the SASB. Firms not classified as *Brown* or *Green* are designated *Neutral*. We estimate Equation 2 separately for each of these three groups. In Panel B, we partition analyst reports in our sample into two groups based on whether the covered firm is included in the Environmental Survey and Reporting (ESR) database in 2011, the year before the implementation of the monitoring program. ESR is the most comprehensive firm-level emissions database and contains firms with the highest levels of emissions. We estimate Equation 2 separately for analyst reports covering firms included in ESR (*Brown* firms) and those covering firms not included in ESR (*Not Brown* firms). *Air Pollution Discussed* is an indicator variable that equals one if the analyst's report discusses air quality as defined by the SASB and measured using a large language model (*DeepSeek-R1*). *Treated* is an indicator variable that equals one for treated analysts in each cohort and zero for control analysts in the cohort. *Post* is an indicator variable that equals one for both treated and control analysts in the cohort starting in the first quarter when the treated analyst's city implements the monitoring program and remains one for all subsequent quarters. All variables are defined in the Variable Appendix. Standard errors are clustered at the City × Year level and reported in parentheses. *, **, *** indicate statistical significance at the 10%, 5%, and 1% levels (two-sided), respectively.

Table 7. Analyst outputs

The model estimated:

$$y_{i,j,q,c} = \beta Treated_{i,c} \times Post_{q,c} + \gamma Controls + \alpha_{j,q,c} + \alpha_{i,j,c} + \varepsilon_{i,j,q,c}$$

where, i, j, q, and c index analysts, firms, calendar year-quarters, and treatment cohorts, respectively.

Panel A. Effect of the monitoring program on analyst outputs

$y \Rightarrow$	(1) *EPS Forecast (%)*	(2) *Recommendation*	(3) *Target Price*	(4) *Report Tone*
Treated × *Post*	0.018	0.000	0.008	0.001
	(0.021)	(0.018)	(0.033)	(0.009)
Observations (Analyst Report-Cohort Level)	67,071	65,389	21,705	67,389
Number of Unique Analysts	715	711	563	715
Number of Unique Firms	1,458	1,443	1,113	1,460
Firm × Year-Quarter × Cohort FE	Yes	Yes	Yes	Yes
Analyst × Firm × Cohort FE	Yes	Yes	Yes	Yes
Adj. R^2	96.6%	78.6%	76.9%	47.3%
Pre-program Mean of y	4.612	4.331	1.241	−0.037
Pre-program Standard Deviation of y	3.077	0.599	0.602	0.290

Table 7 (Continued)

Panel B. Heterogeneity tests - LLM-based classification

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
$y \Rightarrow$	*EPS Forecast (%)*			*Recommendation*			*Target Price*			*Report Tone*		
LLM-based classification $\Rightarrow$	*Green*	*Neutral*	*Brown*	*Green*	*Neutral*	*Brown*	*Green*	*Neutral*	*Brown*	*Green*	*Neutral*	*Brown*
Treated × *Post*	0.284***	0.042	−0.440***	0.152***	0.002	−0.165***	0.137**	0.007	−0.129**	0.081***	−0.001	−0.063**
	(0.096)	(0.031)	(0.114)	(0.054)	(0.018)	(0.031)	(0.046)	(0.036)	(0.037)	(0.026)	(0.012)	(0.014)
p-value for $\beta_{Green} - \beta_{Neutral} > 0$		0.010			0.001			0.011			0.002	
p-value for $\beta_{Neutral} - \beta_{Brown} > 0$		0.000			0.000			0.007			0.001	
p-value for $\beta_{Green} - \beta_{Brown} > 0$		0.000			0.000			0.000			0.000	
Obs. (Analyst Report-Cohort Level)	7,311	52,642	7,118	7,110	51,218	7,061	2,268	17,633	1,804	7,353	52,876	7,160
Number of Unique Analysts	291	684	257	291	680	257	198	520	170	292	684	257
Number of Unique Firms	183	1,127	148	183	1,112	148	135	864	114	184	1,127	149
Firm × Year-Quarter × Cohort FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Analyst × Firm × Cohort FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adj. R^2	96.4%	97.3%	91.1%	75.0%	79.0%	79.4%	84.3%	74.9%	84.5%	45.0%	46.9%	51.5%
Pre-program Mean of y	4.459	4.491	5.609	4.355	4.328	4.333	1.200	1.239	1.309	−0.048	−0.042	0.008
Pre-program Standard Deviation of y	2.779	3.094	3.048	0.583	0.603	0.591	0.531	0.603	0.659	0.285	0.291	0.283

Table 7 (Continued)

Panel C. Heterogeneity tests - Government-designated classification

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$y \Rightarrow$	*EPS Forecast (%)*		*Recommendation*		*Target Price*		*Report Tone*	
Government-designated classification $\Rightarrow$	*Not Brown*	*Brown*	*Not Brown*	*Brown*	*Not Brown*	*Brown*	*Not Brown*	*Brown*
Treated × *Post*	0.040	−0.125**	0.021	−0.125***	0.027	−0.147**	0.009	−0.043**
	(0.025)	(0.044)	(0.016)	(0.038)	(0.041)	(0.065)	(0.009)	(0.017)
p-value for $\beta_{Not\ Brown} - \beta_{Brown} > 0$	0.002		0.000		0.030		0.000	
Observations (Analyst Report-Cohort Level)	54,949	12,122	53,663	11,726	17,958	3,747	55,182	12,207
Number of Unique Analysts	690	462	687	459	534	302	690	462
Number of Unique Firms	1,105	353	1,093	350	855	258	1,107	353
Firm × Year-Quarter × Cohort FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Analyst × Firm × Cohort FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adj. R^2	96.8%	95.6%	79.1%	76.3%	76.6%	78.6%	47.5%	46.1%
Pre-program Mean of y	4.673	4.341	4.336	4.311	1.248	1.208	−0.031	−0.061
Pre-program Standard Deviation of y	3.171	2.609	0.600	0.598	0.609	0.565	0.292	0.283

Table 7 (Continued)

Notes: This table reports the effect of the monitoring program on analyst outputs. Panel A reports evidence on the effects of the monitoring program on analyst outputs using a stacked cohort DiD design. In Panel B, we partition analyst reports into three groups: *Brown*, *Neutral*, and *Green*. We instruct *DeepSeek-Reasoner* to focus exclusively on the firm's business description in the MD&A section of the annual reports of 2011 and to classify a firm as *Brown* (*Green*) if its description indicates that the firm faces risks or costs (gains an advantage or opportunity) from heightened attention to air quality issues, as defined by the SASB. Firms not classified as *Brown* or *Green* are designated *Neutral*. We estimate Equation 2 separately for each of these three groups. In Panel C, we partition analyst reports in our sample into two groups based on whether the covered firm is included in the Environmental Survey and Reporting (ESR) database in 2011, the year before the implementation of the monitoring program. We estimate Equation 2 separately for analyst reports covering firms included in ESR (*Brown* firms) and those covering firms not included in ESR (*Not Brown* firms). *EPS Forecast* is defined as the analyst's EPS forecast, scaled by the firm's stock price at the beginning of the fiscal year, multiplied by 100. *Recommendation* is the analyst's stock recommendation, coded as an ordinal variable ranging from 1 to 5, where 5 indicates a Strong Buy and 1 indicates a Strong Sell. *Target Price* is the ratio of the analyst's target price to the firm's actual stock price at the beginning of the fiscal year. *Report Tone* is calculated as (Positive - Negative) / (Positive + Negative), where Negative (Positive) represents the word count frequency of negative (positive) words in the analyst report as obtained from the CNRDS dataset. Negative and positive words are identified using the Loughran-McDonald dictionary. *Market Reaction* is the (signed) cumulative abnormal return over a three-day window centered on the analyst report date, multiplied by 100. *Treated* is an indicator variable that equals one for treated analysts in each cohort and zero for control analysts in the cohort. *Post* is an indicator variable that equals one for both treated and control analysts in the cohort starting in the first quarter when the treated analyst's city implements the monitoring program and remains one for all subsequent quarters. All variables are defined in the Variable Appendix. Standard errors are clustered at the City × Year level and reported in parentheses. *, **, *** indicate statistical significance at the 10%, 5%, and 1% levels (two-sided), respectively.

Table 8. Site visits

The model estimated:

$$y_{i,j,q,c} = \beta \ Treated_{i,c} \times Post_{q,c} + \alpha_{j,q,c} + \alpha_{i,j,c} + \varepsilon_{i,j,q,c}$$

where, i, j, q, and c index analysts, firms, calendar year-quarters, and treatment cohorts, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
$y \Rightarrow$			*Site Visit*			
Heterogeneity tests $\Rightarrow$	*Full Sample*	*LLM-based classification*			*Government-designated classification*	
		Green	*Neutral*	*Brown*	*Not Brown*	*Brown*
Treated × *Post*	0.022***	0.046***	0.013	0.078**	0.014*	0.050**
	(0.006)	(0.016)	(0.009)	(0.036)	(0.009)	(0.022)
p-value for $\beta_{Green} - \beta_{Neutral} > 0$			0.048			
p-value for $\beta_{Brown} - \beta_{Neutral} > 0$			0.054			
p-value for $\beta_{Green} - \beta_{Brown} > 0$			0.885			
p-value for $\beta_{Brown} - \beta_{Not\ Brown} > 0$					0.095	
Obs. (Firm-Analyst-Year-Quarter-Cohort)	63,747	7,643	50,938	5,166	49,496	14,251
Number of Unique Analysts	657	234	608	180	625	367
Number of Unique Firms	929	125	726	78	683	246
Firm × Year-Quarter × Cohort FE	Yes	Yes	Yes	Yes	Yes	Yes
Analyst × Firm × Cohort FE	Yes	Yes	Yes	Yes	Yes	Yes
Adj. R^2	38.9%	31.5%	42.2%	20.1%	39.5%	36.3%
Pre-program Mean of y	0.017	0.015	0.014	0.051	0.014	0.029
Pre-program Standard Deviation of y	0.131	0.122	0.119	0.220	0.119	0.167

Notes: This table reports the effect of the monitoring program on analyst corporate site visits. *Site Visit* is an indicator variable that equals one if the lead analyst or any of their team members visits the covered firm during the quarter, zero otherwise. The sample is at the firm-analyst-year-quarter-cohort level. Column 1 reports evidence on the effects of the monitoring program on corporate site visits using a stacked cohort DiD design. In Columns 2–4, we partition analyst reports into three groups: *Brown*, *Neutral*, and *Green*. We instruct *DeepSeek-Reasoner* to focus exclusively on the firm's business description in the MD&A section of the annual reports of 2011 and to classify a firm as *Brown* (*Green*) if its description indicates that the firm faces risks or costs (gains an advantage or opportunity) from heightened attention to air quality issues, as defined by the SASB. Firms not classified as *Brown* or *Green* are designated *Neutral*. We estimate separate regressions for each of these three groups. In Columns 5 and 6, we partition analyst reports in our sample into two groups based on whether the covered firm is included in the Environmental Survey and Reporting (ESR) database in 2011, the year before the implementation of the monitoring program. We estimate Equation 2 separately for analyst reports covering firms included in ESR (*Brown* firms) and those covering firms not included in ESR (*Not Brown* firms). *Treated* is an indicator variable that equals one for treated analysts in each cohort and zero for control analysts in the cohort. *Post* is an indicator variable that equals one for both treated and control analysts in the cohort starting in the first quarter when the treated analyst's city implements the monitoring program and remains one for all subsequent quarters. All variables are defined in the Variable Appendix. Standard errors are clustered at the City × Year level and reported in parentheses. *, **, *** indicate statistical significance at the 10%, 5%, and 1% levels (two-sided), respectively.

Table 9. Market reaction to analyst reports

The model estimated:

$$y_{i,j,q,c} = \beta \, Treated_{i,c} \times Post_{q,c} + \alpha_{j,q,c} + \alpha_{i,j,c} + \varepsilon_{i,j,q,c}$$

where, i, j, q, and c index analysts, firms, calendar year-quarters, and treatment cohorts, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
$y \Rightarrow$			*Market Reaction (%)*			
Heterogeneity tests $\Rightarrow$	*Full Sample*	*LLM-based classification*			*Government-designated classification*	
		Green	*Neutral*	*Brown*	*Not Brown*	*Brown*
Treated × *Post*	−0.119	0.864**	−0.119	−1.154***	0.077	−1.372***
	(0.187)	(0.391)	(0.214)	(0.306)	(0.195)	(0.407)
p-value for $\beta_{Green} - \beta_{Neutral} > 0$			0.009			
p-value for $\beta_{Neutral} - \beta_{Brown} > 0$			0.003			
p-value for $\beta_{Green} - \beta_{Brown} > 0$			0.000			
p-value for $\beta_{Not\ Brown} - \beta_{Brown} > 0$					0.000	
Obs. (Analyst Report-Cohort Level)	56,688	6,296	44,450	5,942	46,400	10,288
Number of Unique Analysts	713	291	681	255	689	460
Number of Unique Firms	1,448	184	1,117	147	1,100	348
Firm × Year-Quarter × Cohort FE	Yes	Yes	Yes	Yes	Yes	Yes
Analyst × Firm × Cohort FE	Yes	Yes	Yes	Yes	Yes	Yes
Adj. R^2	32.1%	26.4%	33.2%	28.8%	32.3%	30.7%
Pre-program Mean of y	0.975	0.838	1.010	0.858	0.950	1.080
Pre-program Standard Deviation of y	4.724	4.729	4.746	4.554	4.697	4.834

Notes: This table reports the effect of the monitoring program on market reaction to analyst reports. *Market Reaction (%)* is the (signed) cumulative abnormal return over a three-day window centered on the analyst report date, multiplied by 100. Column 1 reports evidence on the effects of the monitoring program on market reaction to analyst reports using a stacked cohort DiD design. In Columns 2–4, we partition analyst reports into three groups: *Brown*, *Neutral*, and *Green*. We instruct *DeepSeek-Reasoner* to focus exclusively on the firm's business description in the MD&A section of the annual reports of 2011 and to classify a firm as *Brown* (*Green*) if its description indicates that the firm faces risks or costs (gains an advantage or opportunity) from heightened attention to air quality issues, as defined by the SASB. Firms not classified as *Brown* or *Green* are designated *Neutral*. We estimate Equation 2 separately for each of these three groups. In Columns 5 and 6, we partition analyst reports in our sample into two groups based on whether the covered firm is included in the Environmental Survey and Reporting (ESR) database in 2011, the year before the implementation of the monitoring program. We estimate Equation 2 separately for analyst reports covering firms included in ESR (*Brown* firms) and those covering firms not included in ESR (*Not Brown* firms). *Treated* is an indicator variable that equals one for treated analysts in each cohort and zero for control analysts in the cohort. *Post* is an indicator variable that equals one for both treated and control analysts in the cohort starting in the first quarter when the treated analyst's city implements the monitoring program and remains one for all subsequent quarters. All variables are defined in the Variable Appendix. Standard errors are clustered at the City × Year level and reported in parentheses. *, **, *** indicate statistical significance at the 10%, 5%, and 1% levels (two-sided), respectively.

Table 10. Stock return reversal

The model estimated:

$$y_{i,j,q,c} = \beta_1 \, Treated_{i,c} \times Post_{q,c} \times Market\ Reaction_{i,j,q,c} + \beta_2 \, Treated_{i,c} \times Post_{q,c} + \beta_3 \, Treated_{i,c} \times Market\ Reaction_{i,j,q,c} + \beta_4 \, Post_{q,c} \times Market\ Reaction_{i,j,q,c} + \beta_5 \, Market\ Reaction_{i,j,q,c} + \alpha_{j,q,c} + \alpha_{i,j,c} + \varepsilon_{i,j,q,c}$$

where, i, j, q, and c index analysts, firms, calendar year-quarters, and treatment cohorts, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
$y \Rightarrow$		*Post-Analyst-Report BHAR (%)*				
Heterogeneity tests $\Rightarrow$	*Full Sample*	*LLM-based classification*			*Government-designated classification*	
		Green	*Neutral*	*Brown*	*Not Brown*	*Brown*
Treated × *Post* × *Market Reaction (%)*	0.056	−0.423	0.117	0.149	0.079	−0.068
	(0.085)	(0.413)	(0.071)	(0.211)	(0.083)	(0.186)
Treated × *Post*	0.010	−1.392	0.061	1.199	−0.168	1.062
	(0.364)	(1.022)	(0.359)	(0.811)	(0.362)	(0.936)
Treated × *Market Reaction (%)*	−0.012	0.191	−0.032	−0.093	−0.020	0.026
	(0.041)	(0.136)	(0.040)	(0.132)	(0.030)	(0.134)
Post × *Market Reaction (%)*	−0.139*	0.442	−0.235***	−0.010	−0.145*	−0.114
	(0.070)	(0.281)	(0.060)	(0.171)	(0.074)	(0.126)
Market Reaction (%)	−0.289***	−0.599***	−0.264***	−0.134	−0.281***	−0.327***
	(0.055)	(0.160)	(0.053)	(0.164)	(0.063)	(0.103)
Obs. (Analyst Report-Cohort Level)	56,688	6,296	44,450	5,942	46,400	10,288
Number of Unique Analysts	713	291	681	255	689	460
Number of Unique Firms	1,448	184	1,117	147	1,100	348
Firm × Year-Quarter × Cohort FE	Yes	Yes	Yes	Yes	Yes	Yes
Analyst × Firm × Cohort FE	Yes	Yes	Yes	Yes	Yes	Yes
Adj. R^2	94.1%	94.5%	94.0%	94.5%	94.3%	92.9%
Pre-program Mean of y	−0.791	−1.645	−0.088	−4.968	−0.377	−2.581
Pre-program Standard Deviation of y	27.770	27.145	28.374	23.267	27.546	28.649

Table 10 (Continued)

Notes: This table examines the return reversal of market reaction to analyst reports. A negative correlation between the *Market Reaction* to a report and post-analyst-report long-term BHAR returns captures return reversal. *Market Reaction (%)* is the signed cumulative abnormal return over a three-day window centered on the analyst report date, multiplied by 100. We demean *Market Reaction (%)* to facilitate the interpretation of the coefficients on *Treated* × *Post* in this Table. *Post-Analyst-Report BHAR (%)* is the signed buy-and-hold abnormal return of the covered firm over the window starting from the second trading day after the analyst report date and ending 12 months after the analyst report date, multiplied by 100. Column 1 reports the results from a test exploring the change in return reversal for treated analysts from before to after the rollout of the monitoring program in their city, relative to control analysts. In Columns 2–4, we partition analyst reports into three groups: *Brown*, *Neutral*, and *Green*. We instruct *DeepSeek-Reasoner* to focus exclusively on the firm's business description in the MD&A section of the annual reports of 2011 and to classify a firm as *Brown* (*Green*) if its description indicates that the firm faces risks or costs (gains an advantage or opportunity) from heightened attention to air quality issues, as defined by the SASB. Firms not classified as *Brown* or *Green* are designated *Neutral*. We estimate separate regressions for analyst reports covering firms in each of these three groups. In Columns 5 and 6, we partition analyst reports in our sample into two groups based on whether the covered firm is included in the Environmental Survey and Reporting (ESR) database in 2011, the year before the implementation of the monitoring program. We estimate Equation 2 separately for analyst reports covering firms included in ESR (*Brown* firms) and those covering firms not included in ESR (*Not Brown* firms). *Treated* is an indicator variable that equals one for treated analysts in each cohort and zero for control analysts in the cohort. *Post* is an indicator variable that equals one for both treated and control analysts in the cohort starting in the first quarter when the treated analyst's city implements the monitoring program and remains one for all subsequent quarters. All variables are defined in the Variable Appendix. Standard errors are clustered at the City × Year level and reported in parentheses. *, **, *** indicate statistical significance at the 10%, 5%, and 1% levels (two-sided), respectively.

Table 11. Stock price efficiency

The model estimated:

$$y_{i,q} = \beta \ \textit{Treated Analyst Ratio}_{i,q} + \alpha_i + \alpha_q + \varepsilon_{i,q}$$

where, i and q index firms and calendar year-quarters, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
$y \Rightarrow$	*Market Reaction to Earnings Announcement (%)*					
Heterogeneity tests $\Rightarrow$	*Full Sample*	*LLM-based classification*			*Government-designated classification*	
		Green	*Neutral*	*Brown*	*Not Brown*	*Brown*
Treated Analyst Ratio	−0.014	−0.516**	0.120	−0.531**	0.137	−0.503***
	(0.085)	(0.228)	(0.096)	(0.260)	(0.095)	(0.184)
p-value for $\beta_{Green} - \beta_{Neutral} < 0$			0.005			
p-value for $\beta_{Brown} - \beta_{Neutral} < 0$			0.009			
p-value for $\beta_{Green} - \beta_{Brown} < 0$			0.518			
p-value for $\beta_{Brown} - \beta_{Not\ Brown} < 0$					0.001	
Obs. (Firm-Year-Quarter Level)	12,287	1,484	9,464	1,339	9,624	2,663
Number of Unique Firms	1,459	184	1,126	149	1,106	353
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Year-Quarter FE	Yes	Yes	Yes	Yes	Yes	Yes
Adj. R^2	7.6%	5.7%	7.8%	8.4%	8.4%	4.9%
Mean of y	3.325	3.323	3.366	3.035	3.349	3.239
Standard Deviation of y	3.102	2.999	3.141	2.910	3.131	2.991

Notes: This table examines the effect of the monitoring program on stock price efficiency. The sample used in the table is constructed at the firm-year-quarter level over the 2010–2013 period. We measure stock price efficiency using an inverse measure: the market reaction to quarterly earnings announcements. The dependent variable is the absolute cumulative abnormal return over a three-day window centered on the quarterly earnings announcement date, multiplied by 100. Daily abnormal returns are measured as the firm's stock return minus the equally-weighted market return. *Treated Analyst Ratio* is defined as the proportion of treated analysts covering the firm divided by the total number of analysts covering the firm, measured at the beginning of the quarter. We standardize this measure to have a mean of zero and a standard deviation of one. Column 1 reports evidence on the effect of the monitoring program on market reaction to quarterly earnings announcements. In Columns 2-4, we partition firms into three groups: *Brown*, *Neutral*, and *Green*. We instruct *DeepSeek-Reasoner* to focus exclusively on the firm's business description in the MD&A section of the annual reports of 2011 and to classify a firm as *Brown* (*Green*) if its description indicates that the firm faces risks or costs (gains an advantage or opportunity) from heightened attention to air quality issues, as defined by the SASB. Firms not classified as *Brown* or *Green* are designated *Neutral*. We estimate separate regressions for each of these three groups. In Columns 5 and 6, we partition firms in our sample into two groups based on whether the firm is included in the Environmental Survey and Reporting (ESR) database in 2011, the year before the implementation of the monitoring program. We estimate separate regressions for firms included in ESR (*Brown* firms) and those not included in ESR (*Not Brown* firms). All variables are defined in the Variable Appendix. Standard errors are clustered at the Firm level and reported in parentheses. *, **, *** indicate statistical significance at the 10%, 5%, and 1% levels (two-sided), respectively.

Internet Appendix

From the Environment to the Market: How Pollution Monitoring Shapes Financial Analysts' Pricing of Environmental Risks

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Internet Appendix A Variables Definitions

Variable	Definition	Data Source
Heterogeneity Tests: Subsample Limited to Firms in the ESR Dataset [Tables B2]		
Brown Firm–Govt classification (Alternative)	An indicator variable that equals one if the firm's emission intensity is above the median in 2011. The firm's emission intensity measure is calculated as the average of the decile ranks of its NO_x and SO_2 emission intensities within its industry, where these emission intensities are measured as the ratios of the firm's NO_x and SO_2 emissions to sales. We focus on these two pollutants because they are the only ones among the six criteria pollutants covered by the monitoring program.	ESR
Not Brown Firm–Govt classification (Alternative)	An indicator variable that equals one if the firm's emission intensity is below the median in 2011. The firm's emission intensity measure is calculated as the average of the decile ranks of its NO_x and SO_2 emission intensities within its industry, where these emission intensities are measured as the ratios of the firm's NO_x and SO_2 emissions to sales. We focus on these two pollutants because they are the only ones among the six criteria pollutants covered by the monitoring program.	ESR
Stock return reversal over one month following the analyst report date [Tables B4]		
Post-Analyst-Report 1-Month BHAR (%)	Measured as the signed buy-and-hold abnormal return (BHAR) of the covered firm over the window starting from the second trading day after the analyst report date and ending 1 month after the analyst report date, multiplied by 100. BHAR is calculated as: $$\text{BHAR}_{i,t_2,T} = \prod_{\tau=t_2}^{T}(1+R_{i,\tau}) - \prod_{\tau=t_2}^{T}(1+E[R_{i,\tau}])$$ where $R_{i,\tau}$ is the daily stock return of firm i on day τ, $E[R_{i,\tau}]$ is the equally-weighted market return on day τ, t_2 is the second trading day after the analyst report date, and T is the last trading day of the 1-calendar month after the analyst report date. We exclude analyst reports issued on firms' annual earnings announcement dates to avoid capturing market reactions driven by earnings announcements rather than analyst reports.	CSMAR

Profitability of Stock Recommendation [Tables B5]		
Profitability of Stock Recommendation (%)	We measure *Profitability of Stock Recommendation (%)* as follows. We first calculate the buy-and-hold return over the three-day window around the analyst recommendation issuance date, minus the corresponding equally-weighted market buy-and-hold return over the same period. For recommendation revisions made within one year, we invest \$1 in the firm's stock following recommendation upgrades and short \$1 following downgrades. If no prior recommendation has been issued within one year, or if the current recommendation reiterates the prior one after more than one year, the recommendation is treated as an initiation. For recommendation initiations within one year, we invest \$1 for "Strong Buy" and "Buy," \$0 for "Neutral," and short \$1 for "Strong Sell" or "Sell." We multiply the buy-and-hold abnormal return by the corresponding investment position to obtain the profitability measure. We multiply this measure by 100.	CSMAR
Cross-Listed Tests [Table B6]		
Mainland China	An indicator variable that equals one if an analyst lives in mainland China and zero if the analyst resides outside mainland China (e.g., the U.S. or Hong Kong).	
Alternative Post	An indicator variable that equals one for the quarters after the fourth quarter of 2013, and zero for the quarters before the first quarter of 2012.	
Additional Heterogeneity Variables [Tables B7]		
City with a U.S. Embassy or Consulate	An indicator variable equal to one if a city hosts a U.S. embassy or consulate, and zero otherwise. In our sample, Beijing, Guangzhou, and Shanghai host a U.S. embassy or consulate and belong to cohorts 1, 2, and 3, respectively. We also assign this indicator a value of one for all control analyst reports in cohorts 1, 2, and 3.	
Below-Median Analyst Age	An indicator variable that equals one if the analyst's age is below the median analyst's age in 2011, before the program is implemented. The analyst's age is calculated as 2011 minus the year of their college entrance plus 18, i.e., assuming analysts enter college at the age of 18.	CNRDS
Star Analyst	An indicator variable that equals one if the analyst receives the Best Analyst Award from the New Fortune in 2011.	CNRDS

Alternative Proxy for Air Pollution and Social Discussions in Analyst Reports [Table B8]		
Air Pollution Discussed–Dict	An indicator variable that equals one if the analyst report contains air pollution-related words and phrases from a pollution dictionary developed by Lin et al. (2024). Lin et al. (2024) develop a *Pollution and Waste* dictionary that captures air quality along with other topics such as waste management and water treatment. Since our focus is on air quality, we select a subset of keywords from their dictionary that pertain to this topic. Specifically, we instruct *DeepSeek-R1* to evaluate the relevance of each keyword based on the SASB's definition of air quality and retain the keywords for which *DeepSeek-R1* reports 100% relevance.	CnOpendata
Subsample limited to analyst reports issued for never-treated firms [Table B11]		
Never-treated Firms	Covered firms located in cities that implemented the monitoring program only after the end of our sample period (2013Q3).	The program's rollout dates were manually collected from news media and city yearbooks
Including control variables [Table B14]		
Following History	The natural logarithm of one plus the length of time (in quarters) that the analyst has been following the firm.	CNRDS
Experience	The natural logarithm of one plus the number of quarters since the analyst issued their first report in the CNRDS dataset.	CNRDS
Staggered DiD design [Table B15]		
Post Staggered	An indicator variable that equals one starting from the first quarter in which the monitoring program is implemented in the city where the analyst resides and remains one for all subsequent quarters.	
Distance between the analyst's city and the covered firm's city [Table B16]		
Above-Median Firm-Analyst Distance	An indicator variable that equals one if the distance between the analyst's city and the covered firm's city is above the median.	CSMAR

References

Lin, Y., Shen, R., Wang, J., and Yu, Y. J. (2024). Global evolution of environmental and social disclosure in annual reports. *Journal of Accounting Research*, 62(5):1941–1983.

Internet Appendix B Additional Analyses

B.1 Alternative research design: Cross-listed firms

Our research design, placebo tests, and heterogeneity analyses limit the plausibility that concurrent regulations or events confound our results. Any alternative explanation based on concurrent events would need to simultaneously account for several facts. First, because our models include firm-time fixed effects, any explanation must account for why only some analysts, but not others covering the same firm at the same time, change their reports. Second, the alternative explanation must explain the timing of the change in analyst reports. That is, it needs to explain why analysts who change their reports are precisely those located in cities adopting the monitoring program. Third, it must also explain our heterogeneity results. For instance, it must explain why analysts issue less favorable reports for brown firms but more favorable reports for green firms. Fourth, considering our placebo tests for *Air Pollution Discussed* proxy, the alternative explanation would need to impact only air pollution discussions without affecting social topics. We are not aware of any concurrent events that coincide with the staggered timing of the monitoring program across cities, let alone events that meet the above-discussed criteria. However, to further strengthen identification, we adopt a second identification strategy in this section.

Our main identification strategy exploits the staggered implementation of the monitoring program across Chinese cities. Our second identification strategy complements our main identification strategy because it does not rely on staggered timing. Specifically, we implement a static DiD design based on the geographic location of analysts covering Chinese *cross-listed* firms. We define analysts based in mainland China as the treated group and those based outside mainland China (e.g., in the U.S. or Hong Kong) who follow the same firm as the control group. Unlike our main identification strategy that exploits later-treated analysts as the control group, this research design uses never-treated analysts.

The sample used for this setting includes analyst reports issued between 2008 and 2017, excluding the eight quarters spanning from the first adoption quarter (2012Q1) to the last adoption quarter (2013Q4). Using this sample, we estimate the following regression:

$$y_{i,j,q} = \beta\, Mainland\ China_i \times Alternative\ Post_q + \alpha_{j,q} + \alpha_{i,j} + \varepsilon_{i,j,q} \tag{IA1}$$

where i, j, and q index analysts, firms, and calendar year-quarters, respectively. $y_{i,j,q}$ refers to one of our six proxies for analyst i's report issued for firm j in quarter q: *Air Pollution Discussed*, *EPS*, *Recommendation*, *Target Price*, *Report Tone*, and *Market Reaction*. $Mainland\ China_i$ is an indicator variable that equals one for analysts residing in mainland China and zero for analysts residing outside mainland China. $Alternative\ Post_q$ is an indicator variable that equals one for quarters after the last adoption quarter in 2013Q4 (i.e., the 2014–2017 period) and zero for quarters before the first adoption quarter in 2012Q1 (i.e., the 2008–2011 period). The terms $\alpha_{j,q}$ and $\alpha_{i,j}$ represent Firm × Year-Quarter and Analyst × Firm fixed effects, respectively. Similar to our main identification design, these fixed effects absorb all time-varying firm characteristics and all time-invariant analyst-firm pair effects, allowing us to isolate variation within the same firm and year-quarter across analysts.[27] The coefficient of interest, β, measures the change in reports issued by analysts residing in mainland China around the time of implementation, relative to analysts outside mainland China who cover the same firm during the same period. Table B6 presents the results from estimating Equation IA1 using analysts covering Chinese cross-listed firms. Overall, the results are consistent with our main identification strategy.

[27] Our fixed effects subsume the main effect of *Mainland China* and *Alternative Post*.

References

Davidson, R., and J.G. MacKinnon, 2004, *Econometric theory and methods* (Oxford University Press).

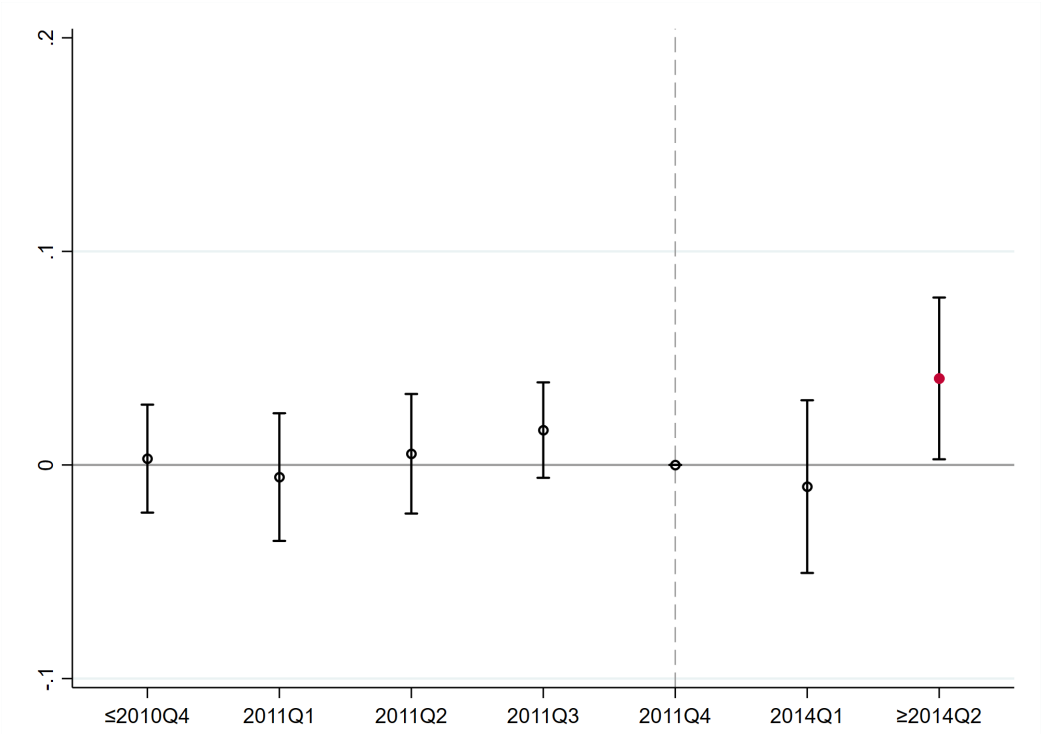
Lin, Yan, Rui Shen, Jasmine Wang, and Y. Julia Yu, 2024, Global evolution of environmental and social disclosure in annual reports, *Journal of Accounting Research* 62, 1941–1983.

Figure B1. Time trend in *Air Quality Discussed* measure using cross-listed sample

The model estimated:

$$y_{i,j,q} = \beta_1 Mainland\ China_i \times Alternative\ PRE + \beta_2 Mainland\ China_i \times Alternative\ POST + \alpha_{j,q} + \alpha_{i,j} + \varepsilon_{i,j,q}$$

where, i, j, and q index analysts, firms, and calendar year-quarters, respectively. *Alternative PRE* is a vector that includes *Alternative Pre*$[\leq 4]_{q,c}$, *Alternative Pre*$[3]_{q,c}$, *Alternative Pre*$[2]_{q,c}$, and *Alternative Pre*$[1]_{q,c}$; and *Alternative POST* is a vector that includes *Alternative Post*$[1]_{q,c}$ and *Alternative Post*$[\geq 2]_{q,c}$.



Notes: This figure presents proxies of analyst discussions of firms' air-polluting activities before and after the monitoring program's implementation. Our sample is at the analyst report level and includes analyst reports issued over the period between 2008 and 2017, excluding the event quarters during which the monitoring program is implemented in China (2012Q1 - 2013Q4). The estimated coefficients are obtained from estimating Equation IA1 modified by replacing *Alternative Post* with a set of indicator variables for quarters before the first implementation quarter in 2012Q1 and after the last implementation quarter in 2013Q4, except the base quarter (the base quarter is the fourth quarter in 2011, which is the quarter immediately before the first implementation quarter). *Air Pollution Discussed* is an indicator variable that equals one if the analyst's report discusses air quality. Vertical lines represent the 90% confidence intervals for each parameter estimate using standard errors clustered at the Analyst and Firm levels. Each shaded (unshaded) triangle on the graph represents a significant (insignificant) regression coefficient.

Table B1. Sample selection

Description	Number of Reports	Number of Firms	Number of Analysts
Reports from CnOpendata issued from 2010Q1 through 2015Q4	217,510	2,777	4,384
Remove:			
Reports for which analyst characteristics are missing	(30,599)	(58)	(1,369)
Reports without a disclosed analyst location	(25,287)	(3)	(321)
Analysts issuing reports on the firm only pre- or post- implementation	(111,219)	(1,256)	(1,979)
Analysts issued in or after 2013Q4, the last adoption quarter	(10,455)	0	0
Final report-level sample	**39,950**	**1,460**	**715**
Final stacked cohort-report-level sample	**67,389**	**1,460**	**715**

Notes: This table outlines the sample construction process.

Table B2. Heterogeneity tests: Subsample limited to firms in the ESR dataset

The model estimated:

$$y_{i,j,q,c} = \beta Treated_{i,c} \times Post_{q,c} + \alpha_{j,q,c} + \alpha_{i,j,c} + \varepsilon_{i,j,q,c}$$

where, i, j, q, and c index analysts, firms, calendar year-quarters, and treatment cohorts, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
$y \Rightarrow$	*Air Pollution Discussed*		*EPS Forecast (%)*		*Recommendation*		*Target Price*		*Report Tone*		*Market Reaction (%)*	
Govt-designated classification												
(Alternative) $\Rightarrow$	*Not Brown*	*Brown*	*Not Brown*	*Brown*	*Not Brown*	*Brown*	*Not Brown*	*Brown*	*Not Brown*	*Brown*	*Not Brown*	*Brown*
Treated × *Post*	0.058*	0.114***	0.039	−0.318***	−0.025	−0.241***	−0.012	−0.316***	−0.019	−0.070**	−1.051*	−1.745***
	(0.033)	(0.042)	(0.050)	(0.075)	(0.027)	(0.073)	(0.027)	(0.089)	(0.018)	(0.029)	(0.528)	(0.500)
p-value for $\beta_{Brown} - \beta_{Not\ Brown} > 0$	0.085											
p-value for $\beta_{Not\ Brown} - \beta_{Brown} > 0$			0.001		0.007		0.001		0.056		0.157	
Obs. (Analyst Report-Cohort Level)	6,281	5,926	6,239	5,883	6,005	5,721	1,976	1,771	6,281	5,926	5,284	5,004
Number of Unique Analysts	347	308	347	308	344	307	206	194	347	308	342	307
Number of Unique Firms	179	174	179	174	178	172	130	128	179	174	175	173
Firm × Year-Quarter × Cohort FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Analyst × Firm × Cohort FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adj. R^2	60.3%	39.1%	96.9%	93.5%	75.9%	76.6%	83.4%	75.6%	45.1%	47.3%	35.1%	25.3%
Pre-program Mean of y	0.025	0.013	4.555	4.102	4.334	4.287	1.184	1.236	−0.060	−0.064	0.960	1.213
Pre-program Standard Deviation of y	0.157	0.114	2.728	2.447	0.586	0.611	0.495	0.637	0.284	0.281	4.787	4.884

Table B2 (Continued)

Notes: This table reports results on whether the effect of the monitoring program varies with the firms' pollution levels after limiting the sample to firms included in the ESR dataset. We partition analyst reports in our sample into two groups based on whether a firm's emission intensity is above or below the median in 2011. We estimate Equation 2 separately for analyst reports covering firms with above-median emission intensity (*Brown Firms - Govt classification (Alternative)*) and those covering firms with below-median emission intensity (*Not Brown Firms - Govt classification (Alternative)*). The firm's emission intensity measure is calculated as the average of the decile ranks of its NO_x and SO_2 emission intensities within its industry, where these emission intensities are measured as the ratios of the firm's NO_x and SO_2 emissions to sales. *Air Pollution Discussed* is an indicator variable that equals one if the analyst's report discusses air quality as defined by the SASB and measured using a large language model (*DeepSeek-R1*). *EPS Forecast* is defined as the analyst's EPS forecast, scaled by the firm's stock price at the beginning of the fiscal year, multiplied by 100. *Recommendation* is the analyst's stock recommendation, coded as an ordinal variable ranging from 1 to 5, where 5 indicates a Strong Buy and 1 indicates a Strong Sell. *Target Price* is the ratio of the analyst's target price to the firm's actual stock price at the beginning of the fiscal year. *Report Tone* is calculated as (Positive - Negative) / (Positive + Negative), where Negative (Positive) represents the word count frequency of negative (positive) words in the analyst report as obtained from the CNRDS dataset. Negative and positive words are identified using the Loughran-McDonald dictionary. *Market Reaction (%)* is the (signed) cumulative abnormal return over a three-day window centered on the analyst report date, multiplied by 100. *Treated* is an indicator variable that equals one for treated analysts in each cohort and zero for control analysts in the cohort. *Post* is an indicator variable that equals one for both treated and control analysts in the cohort starting in the first quarter when the treated analyst's city implements the monitoring program and remains one for all subsequent quarters. All variables are defined in the Variable Appendix in the paper or in Table Internet Appendix A. Standard errors are clustered at the City × Year level and reported in parentheses. *, **, *** indicate statistical significance at the 10%, 5%, and 1% levels (two-sided), respectively.

Table B3. Heterogeneity tests for different types of environmental risks

The model estimated:

$$y_{i,j,q,c} = \beta \, Treated_{i,c} \times Post_{q,c} + \alpha_{j,q,c} + \alpha_{i,j,c} + \varepsilon_{i,j,q,c}$$

where, i, j, q, and c index analysts, firms, calendar year-quarters, and treatment cohorts, respectively.

Panel A. Heterogeneity tests for regulatory risks discussed

	(1)	(2)	(3)	(4)	(5)
$y \Rightarrow$	*Regulatory Risks Discussed*				
Heterogeneity tests $\Rightarrow$	*LLM-based classification*			*Government-designated classification*	
	Green	*Neutral*	*Brown*	*Not Brown*	*Brown*
Treated × *Post*	0.090***	0.003	0.057***	0.008**	0.071***
	(0.022)	(0.003)	(0.016)	(0.003)	(0.025)
p-value for $\beta_{Green} - \beta_{Neutral} > 0$		0.000			
p-value for $\beta_{Brown} - \beta_{Neutral} > 0$		0.001			
p-value for $\beta_{Green} - \beta_{Brown} > 0$		0.101			
p-value for $\beta_{Brown} - \beta_{Not\ Brown} > 0$				0.004	
Observations (Analyst Report-Cohort Level)	7,353	52,876	7,160	55,182	12,207
Number of Unique Analysts	292	684	257	690	462
Number of Unique Firms	184	1,127	149	1,107	353
Firm × Year-Quarter × Cohort FE	Yes	Yes	Yes	Yes	Yes
Analyst × Firm × Cohort FE	Yes	Yes	Yes	Yes	Yes
Adj. R^2	38.3%	41.1%	34.7%	40.4%	46.2%
Pre-program Mean of y	0.068	0.010	0.024	0.018	0.017
Pre-program Standard Deviation of y	0.252	0.100	0.154	0.134	0.129

Table B3 (Continued)

Panel B. Heterogeneity tests for preference-related factors discussed

	(1)	(2)	(3)	(4)	(5)
$y \Rightarrow$	*Preference-related Factors Discussed*				
Heterogeneity tests $\Rightarrow$	*LLM-based classification*			*Government-designated classification*	
	Green	*Neutral*	*Brown*	*Not Brown*	*Brown*
Treated × *Post*	0.054**	0.005***	0.033**	0.008***	0.043*
	(0.020)	(0.002)	(0.013)	(0.003)	(0.022)
p-value for $\beta_{Green} - \beta_{Neutral} > 0$		0.006			
p-value for $\beta_{Brown} - \beta_{Neutral} > 0$		0.016			
p-value for $\beta_{Green} - \beta_{Brown} > 0$		0.208			
p-value for $\beta_{Brown} - \beta_{Not\ Brown} > 0$				0.062	
Observations (Analyst Report-Cohort Level)	7,353	52,876	7,160	55,182	12,207
Number of Unique Analysts	292	684	257	690	462
Number of Unique Firms	184	1,127	149	1,107	353
Firm × Year-Quarter × Cohort FE	Yes	Yes	Yes	Yes	Yes
Analyst × Firm × Cohort FE	Yes	Yes	Yes	Yes	Yes
Adj. R^2	45.4%	45.7%	7.1%	50.2%	29.5%
Pre-program Mean of y	0.071	0.008	0.012	0.016	0.015
Pre-program Standard Deviation of y	0.258	0.092	0.108	0.124	0.122

Table B3 (Continued)

Notes: This table reports on the heterogeneity of the effect of the monitoring program on analyst discussions of different types of environmental risks. The dependent variables in Panel A and Panel B are *Regulatory Risks Discussed* and *Preference-related Factors Discussed*, respectively. *Regulatory Risks Discussed* equals one if the analyst discusses environmental regulatory risks. *Preference-related Factors Discussed* equals one if the analyst discusses changes in customer preference and demand driven by pollution or climate concerns. We use *DeepSeek-R1* to classify these discussions based solely on the text of the analyst reports, instructing the model to interpret "risk" broadly as the firm's exposure to pollution- or climate-related factors—such as past, current, or anticipated regulation, physical conditions, or shifts in customer preferences—that may entail adverse consequences (e.g., higher costs, constraints, reduced market share) or positive consequences (e.g., new markets, competitive advantages, cost savings, policy support). In Columns 1–3 of each panel, we partition analyst reports into three groups: *Brown*, *Neutral*, and *Green*. We instruct *DeepSeek-Reasoner* to focus exclusively on the firm's business description in the MD&A section of the annual reports of 2011 and to classify a firm as *Brown* (*Green*) if its description indicates that the firm faces risks or costs (gains an advantage or opportunity) from heightened attention to air quality issues, as defined by the SASB. Firms not classified as *Brown* or *Green* are designated *Neutral*. We estimate separate regressions for each of these three groups. In Columns 4 and 5 of each panel, we partition analyst reports in our sample into two groups based on whether the covered firm is included in the Environmental Survey and Reporting (ESR) database in 2011, the year before the implementation of the monitoring program. We estimate Equation 2 separately for analyst reports covering firms included in ESR (*Brown* firms) and those covering firms not included in ESR (*Not Brown* firms). *Treated* is an indicator variable that equals one for treated analysts in each cohort and zero for control analysts in the cohort. *Post* is an indicator variable that equals one for both treated and control analysts in the cohort starting in the first quarter when the treated analyst's city implements the monitoring program and remains one for all subsequent quarters. All variables are defined in the Variable Appendix. Standard errors are clustered at the City × Year level and reported in parentheses. *, **, *** indicate statistical significance at the 10%, 5%, and 1% levels (two-sided), respectively.

Table B4. Stock return reversal over one month following the analyst report date

The model estimated (only the relevant coefficients are tabulated for brevity):

$$y_{i,j,q,c} = \beta_1 \, Treated_{i,c} \times Post_{q,c} \times Market\ Reaction_{i,j,q,c} + \beta_2 \, Treated_{i,c} \times Post_{q,c} + \beta_3 \, Treated_{i,c} \times Market\ Reaction_{i,j,q,c} + \beta_4 \, Post_{q,c} \times Market\ Reaction_{i,j,q,c} + \beta_5 \, Market\ Reaction_{i,j,q,c} + \alpha_{j,q,c} + \alpha_{i,j,c} + \varepsilon_{i,j,q,c}$$

where, i, j, q, and c index analysts, firms, calendar year-quarters, and treatment cohorts, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
$y \Rightarrow$	*Post-Analyst-Report 1-Month BHAR (%)*					
Heterogeneity tests $\Rightarrow$	*Full Sample*	*LLM-based classification*			*Government-designated classification*	
		Green	*Neutral*	*Brown*	*Not Brown*	*Brown*
Treated × *Post* × *Market Reaction (%)*	−0.049	−0.280	−0.047	0.145	−0.042	−0.084
	(0.082)	(0.327)	(0.075)	(0.244)	(0.075)	(0.190)
Treated × *Post*	−0.286	−1.331	−0.194	−0.021	−0.095	−1.577***
	(0.272)	(0.852)	(0.255)	(0.623)	(0.286)	(0.522)
Treated × *Market Reaction (%)*	0.018	0.072	0.032	−0.148	0.011	0.050
	(0.027)	(0.131)	(0.033)	(0.103)	(0.029)	(0.057)
Post × *Market Reaction (%)*	−0.033	0.423	−0.058	−0.335	−0.051	0.048
	(0.066)	(0.352)	(0.073)	(0.259)	(0.074)	(0.143)
Market Reaction (%)	−0.150***	−0.395	−0.129*	−0.041	−0.128*	−0.255***
	(0.056)	(0.237)	(0.072)	(0.118)	(0.068)	(0.070)
Obs. (Analyst Report-Cohort Level)	56,544	6,289	44,319	5,936	46,273	10,271
Number of Unique Analysts	713	291	681	255	689	460
Number of Unique Firms	1,448	184	1,117	147	1,100	348
Firm × Year-Quarter × Cohort FE	Yes	Yes	Yes	Yes	Yes	Yes
Analyst × Firm × Cohort FE	Yes	Yes	Yes	Yes	Yes	Yes
Adj. R^2	42.6%	35.0%	43.4%	44.4%	43.3%	38.8%
Pre-program Mean of y	−0.502	−0.291	−0.393	−1.491	−0.503	−0.497
Pre-program Standard Deviation of y	8.416	8.538	8.379	8.486	8.358	8.659

Table B4 (Continued)

Notes: This table examines the return reversal of market reaction to analyst reports. A negative correlation between the *Market Reaction* to a report and post-analyst-report long-term BHAR returns captures return reversal. *Market Reaction (%)* is the signed cumulative abnormal return over a three-day window centered on the analyst report date, multiplied by 100. We demean *Market Reaction (%)* to facilitate the interpretation of the coefficients on *Treated* × *Post* in this Table. *Post-Analyst-Report 1-Month BHAR (%)* is defined similarly to *Post-Analyst-Report BHAR (%)* except that we use 1 month rather than 12 months to measure post-analyst-report returns. Specifically, *Post-Analyst-Report 1-Month BHAR (%)* is the signed buy-and-hold abnormal return of the covered firm over the window starting from the second trading day after the analyst report date and ending one month after the analyst report date, multiplied by 100. Column 1 reports the results from a test exploring the change in return reversal for treated analysts from before to after the rollout of the monitoring program in their city, relative to control analysts. In Columns 2–4, we partition analyst reports into three groups: *Brown*, *Neutral*, and *Green*. We instruct *DeepSeek-Reasoner* to focus exclusively on the firm's business description in the MD&A section of the annual reports of 2011 and to classify a firm as *Brown* (*Green*) if its description indicates that the firm faces risks or costs (gains an advantage or opportunity) from heightened attention to air quality issues, as defined by the SASB. Firms not classified as *Brown* or *Green* are designated *Neutral*. We estimate separate regressions for analyst reports covering firms in each of these three groups. In Columns 5 and 6, we partition analyst reports in our sample into two groups based on whether the covered firm is included in the Environmental Survey and Reporting (ESR) database in 2011, the year before the implementation of the monitoring program. We estimate Equation 2 separately for analyst reports covering firms included in ESR (*Brown* firms) and those covering firms not included in ESR (*Not Brown* firms). *Treated* is an indicator variable that equals one for treated analysts in each cohort and zero for control analysts in the cohort. *Post* is an indicator variable that equals one for both treated and control analysts in the cohort starting in the first quarter when the treated analyst's city implements the monitoring program and remains one for all subsequent quarters. All variables are defined in the Variable Appendix in the paper or in Table Internet Appendix A. Standard errors are clustered at the City × Year level and reported in parentheses. *, **, *** indicate statistical significance at the 10%, 5%, and 1% levels (two-sided), respectively.

Table B5. Profitability of stock recommendation

The model estimated

$$y_{i,j,q,c} = \beta \ Treated_{i,c} \times Post_{q,c} + \alpha_{j,q,c} + \alpha_{i,j,c} + \varepsilon_{i,j,q,c}$$

where, i, j, q, and c index analysts, firms, calendar year-quarters, and treatment cohorts, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
$y \Rightarrow$	*Profitability of Stock Recommendation (%)*					
Heterogeneity tests $\Rightarrow$	*Full Sample*	*LLM-based classification*			*Government-designated classification*	
		Green	*Neutral*	*Brown*	*Not Brown*	*Brown*
Treated × *Post*	0.253*	1.394***	−0.010	1.175*	0.142	0.960**
	(0.132)	(0.378)	(0.186)	(0.659)	(0.150)	(0.405)
p-value for $\beta_{Green} - \beta_{Neutral} > 0$			0.003			
p-value for $\beta_{Brown} - \beta_{Neutral} > 0$			0.055			
p-value for $\beta_{Green} - \beta_{Brown} > 0$			0.362			
p-value for $\beta_{Brown} - \beta_{Not\ Brown} > 0$					0.036	
Obs. (Analyst Report-Cohort Level)	54,743	6,057	42,837	5,849	44,923	9,820
Number of Unique Analysts	709	289	677	255	686	456
Number of Unique Firms	1,428	183	1,099	146	1,085	343
Firm × Year-Quarter × Cohort FE	Yes	Yes	Yes	Yes	Yes	Yes
Analyst × Firm × Cohort FE	Yes	Yes	Yes	Yes	Yes	Yes
Adj. R^2	19.1%	12.9%	20.0%	18.0%	19.6%	16.3%
Pre-program Mean of y	0.756	0.709	0.771	0.692	0.740	0.822
Pre-program Standard Deviation of y	4.302	4.389	4.273	4.421	4.294	4.339

Notes: This table examines the effect of the monitoring program on the profitability of analysts' stock recommendations. The dependent variable, *Profitability of Stock Recommendation (%)*, is measured as follows. We first calculate the buy-and-hold return over the three-day window around the analyst recommendation issuance date, minus the corresponding equally-weighted market buy-and-hold return over the same period. For recommendation revisions made within one year, we invest \$1 in the firm's stock following recommendation upgrades and short \$1 following downgrades. If no prior recommendation has been issued within one year, or if the current recommendation reiterates the prior one after more than one year, the recommendation is treated as an initiation. For recommendation initiations within one year, we invest \$1 for "Strong Buy" and "Buy," \$0 for "Neutral," and short \$1 for "Strong Sell" or "Sell." We multiply the buy-and-hold abnormal return by the corresponding investment position to obtain the profitability measure. We multiply this measure by 100. *Treated* is an indicator variable that equals one for treated analysts in each cohort and zero for control analysts in the same cohort. *Post* is an indicator variable that equals one for both treated and control analysts in the cohort starting in the first quarter when the treated analyst's city implements the monitoring program and remains one thereafter. Column 1 reports evidence on the effects of the monitoring program on market reaction to analyst reports using a stacked cohort DiD design. In Columns 2–4, we partition analyst reports into three groups: *Brown*, *Neutral*, and *Green*. We instruct *DeepSeek-Reasoner* to focus exclusively on the firm's business description in the MD&A section of the annual reports of 2011 and to classify a firm as *Brown* (*Green*) if its description indicates that the firm faces risks or costs (gains an advantage or opportunity) from heightened attention to air quality issues, as defined by the SASB. Firms not classified as *Brown* or *Green* are designated *Neutral*. We estimate Equation 2 separately for each of these three groups. In Columns 5 and 6, we partition analyst reports in our sample into two groups based on whether the covered firm is included in the Environmental Survey and Reporting (ESR) database in 2011, the year before the implementation of the monitoring program. We estimate Equation 2 separately for analyst reports covering firms included in ESR (*Brown* firms) and those covering firms not included in ESR (*Not Brown* firms). *Treated* is an indicator variable that equals one for treated analysts in each cohort and zero for control analysts in the cohort. *Post* is an indicator variable that equals one for both treated and control analysts in the cohort starting in the first quarter when the treated analyst's city implements the monitoring program and remains one for all subsequent quarters. All variables are defined in the Variable Appendix in the paper or in Table Internet Appendix A. Standard errors are clustered at the City × Year level and reported in parentheses. *, **, *** indicate statistical significance at the 10%, 5%, and 1% levels (two-sided), respectively.

Table B6. Cross-listed sample tests

The model estimated:

$$y_{i,j,q} = \beta Mainland\ China_i \times Alternative\ Post_q + \alpha_{j,q} + \alpha_{i,j} + \varepsilon_{i,j,q}$$

where, i, j, and q index analysts, firms, and calendar year-quarters, respectively.

Panel A. *Air Pollution Discussed*

	(1)	(2)	(3)	(4)	(5)	(6)
$y \Rightarrow$		*Air Pollution Discussed*				
Heterogeneity tests $\Rightarrow$	*Full Sample*	*LLM-based classification*			*Government-designated classification*	
		Green	*Neutral*	*Brown*	*Not Brown*	*Brown*
Mainland China × *Alternative Post*	0.028**	0.119*	−0.001	0.070***	0.017	0.069*
	(0.012)	(0.060)	(0.014)	(0.019)	(0.014)	(0.031)
p-value for $\beta_{Green} - \beta_{Neutral} > 0$			0.020			
p-value for $\beta_{Brown} - \beta_{Neutral} > 0$			0.002			
p-value for $\beta_{Green} - \beta_{Brown} > 0$			0.228			
p-value for $\beta_{Brown} - \beta_{Not\ Brown} > 0$					0.054	
Observations (Analyst Report Level)	16,781	2,146	12,708	1,927	14,218	2,563
Number of Unique Analysts	1,619	509	1,361	351	1,421	546
Number of Unique Firms	72	8	56	8	62	10
Firm × Year-Quarter FE	Yes	Yes	Yes	Yes	Yes	Yes
Analyst × Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Adj. R^2	24.1%	27.6%	22.2%	12.5%	25.2%	21.7%
Pre-program Mean of y	0.016	0.058	0.006	0.027	0.016	0.014
Pre-program Standard Deviation of y	0.125	0.234	0.079	0.161	0.126	0.117

Table B6 (Continued)

Panel B. *EPS Forecast (%)*

	(1)	(2)	(3)	(4)	(5)	(6)
$y \Rightarrow$			*EPS Forecast (%)*			
Heterogeneity tests $\Rightarrow$	*Full Sample*	*LLM-based classification*			*Government-designated classification*	
		Green	*Neutral*	*Brown*	*Not Brown*	*Brown*
Mainland China × *Alternative Post*	−0.070	0.401*	0.010	−0.619**	0.092	−0.864*
	(0.183)	(0.175)	(0.248)	(0.245)	(0.184)	(0.436)
p-value for $\beta_{Green} - \beta_{Neutral} > 0$			0.087			
p-value for $\beta_{Neutral} - \beta_{Brown} > 0$			0.036			
p-value for $\beta_{Green} - \beta_{Brown} > 0$			0.001			
p-value for $\beta_{NotBrown} - \beta_{Brown} > 0$					0.020	
Observations (Analyst Report Level)	15,538	2,066	11,653	1,819	13,101	2,437
Number of Unique Analysts	1,589	508	1,321	348	1,389	535
Number of Unique Firms	65	8	49	8	55	10
Firm × Year-Quarter FE	Yes	Yes	Yes	Yes	Yes	Yes
Analyst × Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Adj. R^2	93.8%	95.6%	94.9%	80.7%	94.2%	90.1%
Pre-program Mean of y	5.797	4.935	6.131	4.715	5.936	5.025
Pre-program Standard Deviation of y	3.734	2.803	3.915	3.144	3.885	2.622

Panel C. *Recommendation*

	(1)	(2)	(3)	(4)	(5)	(6)
$y \Rightarrow$			*Recommendation*			
Heterogeneity tests $\Rightarrow$	*Full Sample*	*LLM-based classification*			*Government-designated classification*	
		Green	*Neutral*	*Brown*	*Not Brown*	*Brown*
Mainland China × *Alternative Post*	−0.029	0.219*	0.010	−0.325*	0.032	−0.300*
	(0.075)	(0.098)	(0.085)	(0.140)	(0.078)	(0.152)
p-value for $\beta_{Green} - \beta_{Neutral} > 0$			0.044			
p-value for $\beta_{Neutral} - \beta_{Brown} > 0$			0.017			
p-value for $\beta_{Green} - \beta_{Brown} > 0$			0.002			
p-value for $\beta_{NotBrown} - \beta_{Brown} > 0$					0.018	
Observations (Analyst Report Level)	16,487	2,113	12,528	1,846	14,004	2,483
Number of Unique Analysts	1,597	500	1,343	338	1,399	529
Number of Unique Firms	72	8	56	8	62	10
Firm × Year-Quarter FE	Yes	Yes	Yes	Yes	Yes	Yes
Analyst × Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Adj. R^2	73.8%	72.5%	74.2%	68.5%	73.4%	75.6%
Pre-program Mean of y	3.962	4.177	3.953	3.744	3.952	4.021
Pre-program Standard Deviation of y	0.738	0.699	0.728	0.780	0.735	0.752

Table B6 (Continued)

Panel D. *Target Price*

	(1)	(2)	(3)	(4)	(5)	(6)
$y \Rightarrow$			*Target Price*			
Heterogeneity tests $\Rightarrow$	*Full Sample*	*LLM-based classification*			*Government-designated classification*	
		Green	*Neutral*	*Brown*	*Not Brown*	*Brown*
Mainland China × *Alternative Post*	−0.017	0.174***	−0.002	−0.222**	0.029	−0.172*
	(0.055)	(0.038)	(0.068)	(0.083)	(0.056)	(0.086)
p-value for $\beta_{Green} - \beta_{Neutral} > 0$			0.010			
p-value for $\beta_{Neutral} - \beta_{Brown} > 0$			0.020			
p-value for $\beta_{Green} - \beta_{Brown} > 0$			0.000			
p-value for $\beta_{NotBrown} - \beta_{Brown} > 0$					0.020	
Observations (Analyst Report Level)	8,664	1,132	6,324	1,208	7,211	1,453
Number of Unique Analysts	1,086	307	877	232	923	352
Number of Unique Firms	65	8	49	8	55	10
Firm × Year-Quarter FE	Yes	Yes	Yes	Yes	Yes	Yes
Analyst × Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Adj. R^2	80.0%	84.8%	80.2%	74.2%	80.5%	78.2%
Pre-program Mean of y	1.115	1.102	1.151	0.931	1.125	1.063
Pre-program Standard Deviation of y	0.489	0.520	0.471	0.510	0.496	0.445

Panel E. *Report Tone*

	(1)	(2)	(3)	(4)	(5)	(6)
$y \Rightarrow$			*Report Tone*			
Heterogeneity tests $\Rightarrow$	*Full Sample*	*LLM-based classification*			*Government-designated classification*	
		Green	*Neutral*	*Brown*	*Not Brown*	*Brown*
Mainland China × *Alternative Post*	0.032	0.170**	0.047	−0.101**	0.059	−0.075*
	(0.043)	(0.060)	(0.056)	(0.039)	(0.052)	(0.034)
p-value for $\beta_{Green} - \beta_{Neutral} > 0$			0.064			
p-value for $\beta_{Neutral} - \beta_{Brown} > 0$			0.013			
p-value for $\beta_{Green} - \beta_{Brown} > 0$			0.001			
p-value for $\beta_{NotBrown} - \beta_{Brown} > 0$					0.016	
Observations (Analyst Report Level)	16,781	2,146	12,708	1,927	14,218	2,563
Number of Unique Analysts	1,619	509	1,361	351	1,421	546
Number of Unique Firms	72	8	56	8	62	10
Firm × Year-Quarter FE	Yes	Yes	Yes	Yes	Yes	Yes
Analyst × Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Adj. R^2	46.7%	48.0%	45.7%	49.6%	47.4%	43.4%
Pre-program Mean of y	-0.082	-0.068	-0.075	-0.145	-0.083	-0.075
Pre-program Standard Deviation of y	0.304	0.296	0.304	0.301	0.303	0.307

Table B6 (Continued)

Panel F. *Market Reaction (%)*

$y \Rightarrow$	(1)	(2)	(3)	(4)	(5)	(6)
		Market Reaction (%)				
Heterogeneity tests $\Rightarrow$	*Full Sample*	*LLM-based classification*			*Government-designated classification*	
		Green	*Neutral*	*Brown*	*Not Brown*	*Brown*
Mainland China × *Alternative Post*	0.518	1.420	0.736	−1.444*	0.927	−1.874*
	(0.574)	(2.070)	(0.666)	(0.662)	(0.634)	(0.975)
p-value for $\beta_{Green} - \beta_{Neutral} > 0$			0.371			
p-value for $\beta_{Neutral} - \beta_{Brown} > 0$			0.011			
p-value for $\beta_{Green} - \beta_{Brown} > 0$			0.097			
p-value for $\beta_{NotBrown} - \beta_{Brown} > 0$					0.008	
Observations (Analyst Report Level)	14,360	1,886	10,834	1,640	12,068	2,292
Number of Unique Analysts	1,576	492	1,309	338	1,371	530
Number of Unique Firms	66	8	50	8	56	10
Firm × Year-Quarter FE	Yes	Yes	Yes	Yes	Yes	Yes
Analyst × Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Adj. R^2	36.7%	41.2%	34.2%	45.0%	37.6%	32.6%
Pre-program Mean of y	0.409	0.853	0.360	0.137	0.404	0.438
Pre-program Standard Deviation of y	4.517	4.944	4.411	4.599	4.483	4.700

Notes: This table reports evidence of the effects of the monitoring program on several analyst outputs using an alternative identification strategy based on a sample of cross-listed Chinese firms. Our sample is at the analyst report level and includes analyst reports issued over the period between 2008 and 2017, excluding the event quarters during which the monitoring program is implemented (i.e., excluding the eight quarters spanning from the first adoption quarter in 2012Q1 to the last adoption quarter in 2013Q4). For each cross-listed firm, we identify two groups of analysts covering the firm: those based in mainland China and those based outside mainland China (e.g., the U.S.). We examine six dependent variables and report results for each variable in a separate panel: *Air Pollution Discussed* (Panel A), *EPS Forecast (%)* (Panel B), *Recommendation* (Panel C), *Target Price* (Panel D), *Report Tone* (Panel E), and *Market Reaction (%)* (Panel F). *Mainland China* is an indicator variable that equals one for analysts residing in mainland China and zero for analysts residing outside mainland China. *Alternative Post* is an indicator variable that equals one for quarters after the last adoption quarter in 2013Q4 (i.e., the 2014–2017 period) and zero for quarters before the first adoption quarter in 2012Q1 (i.e., the 2008–2011 period). In each panel, Column 1 reports the main results from estimating Equation IA1. In Columns 2–4, we partition analyst reports into three groups: *Brown*, *Neutral*, and *Green*. We instruct *DeepSeek-Reasoner* to focus exclusively on the firm's business description in the M&A section of the annual reports of 2011 and to classify a firm as *Brown* (*Green*) if its description indicates that the firm faces risks or costs (gains an advantage or opportunity) from heightened attention to air quality issues, as defined by the SASB. Firms not classified as *Brown* or *Green* are designated *Neutral*. We estimate Equation IA1 separately for each of these three groups. In Columns 5 and 6, we partition analyst reports in our sample into two groups based on whether the covered firm is included in the Environmental Survey and Reporting (ESR) database in 2011, the year before the implementation of the monitoring program. We estimate Equation IA1 separately for analyst reports covering firms included in ESR (*Brown* firms) and those covering firms not included in ESR (*Not Brown* firms). All variables are defined in the Variable Appendix in the paper or in Table Internet Appendix A. Standard errors are clustered at the Analyst and Firm levels and reported in parentheses. *, **, *** indicate statistical significance at the 10%, 5%, and 1% levels (two-sided), respectively.

Table B7. Additional heterogeneity tests

The model estimated:

$$y_{i,j,q,c} = \beta\, Treated_{i,c} \times Post_{q,c} + \alpha_{j,q,c} + \alpha_{i,j,c} + \varepsilon_{i,j,q,c}$$

where, i, j, q, and c index analysts, firms, calendar year-quarters, and treatment cohorts, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
$y \Rightarrow$	*Air Pollution Discussed*					
Heterogeneity tests $\Rightarrow$	*City with a US Embassy or Consulate*		*Below-Median Analyst Age*		*Star Analyst*	
	No	*Yes*	*No*	*Yes*	*No*	*Yes*
Treated × *Post*	0.034*	0.019***	−0.002	0.044***	0.020**	0.088***
	(0.017)	(0.003)	(0.007)	(0.017)	(0.006)	(0.029)
p-value for $\beta_{No} - \beta_{Yes} > 0$	0.008					
p-value for $\beta_{Yes} - \beta_{No} > 0$			0.011		0.012	
Observations (Analyst Report-Cohort Level)	18,136	61,178	21,619	21,569	50,266	17,123
Number of Unique Analysts	456	715	205	220	632	83
Number of Unique Firms	1223	1,460	971	963	1,399	732
Firm × Year-Quarter × Cohort FE	Yes	Yes	Yes	Yes	Yes	Yes
Analyst × Firm × Cohort FE	Yes	Yes	Yes	Yes	Yes	Yes
Adj. R^2	49.4%	46.4%	50.5%	52.4%	46.9%	46.6%
Pre-program Mean of y	0.021	0.022	0.025	0.020	0.022	0.021
Pre-program Standard Deviation of y	0.144	0.146	0.157	0.140	0.145	0.143

Notes: This table reports results on whether the effect of the monitoring program on analyst discussions of firms' air-pollution activities in their reports varies with three variables: *City with a U.S. Embassy or Consulate*, *Below-Median Analyst Age*, and *Star Analyst*. In **Columns 1 and 2**, we partition treated analyst reports in our sample into two groups based on whether an analyst is located in a city with a U.S. Embassy or Consulate, and estimate Equations 2 separately for these two groups of reports. Cities hosting a U.S. embassy or consulate in our sample are Beijing, Guangzhou, and Shanghai, which belong to cohorts 1, 2, and 3, respectively. Column 2 includes reports issued by analysts in these three cities, along with all control analyst reports in cohorts 1, 2, and 3. Column 1 includes treated analyst reports in cohort 2 other than those issued by analysts in Guangzhou, treated analyst reports in cohort 3 other than those issued by analysts in Shanghai, all control analyst reports in cohorts 2 and 3, and all observations in cohorts 4 and 5. As a result, some control analyst reports, specifically those in cohorts 2 and 3, are included in both columns 1 and 2. Therefore, the sum of the observations in columns 1 and 2 (79,314) exceeds the number of observations in our main sample (67,389). In **Columns 3 and 4**, we use analyst age as of 2011, the year before the implementation of the monitoring program, and partition analyst reports in our sample into two groups based on whether the analyst age is below or above the median analyst age. We estimate Equation 2 separately for these groups. In **Columns 5 and 6**, we partition analyst reports in our sample into two groups based on whether the analyst received the Star Analyst Award from the New Fortune in 2011, and estimate Equation 2 separately for these groups. *Air Pollution Discussed* is an indicator variable that equals one if the analyst's report discusses air quality as defined by the SASB and measured using a large language model (*DeepSeek-R1*). *Treated* is an indicator variable that equals one for treated analysts in each cohort and zero for control analysts in the cohort. *Post* is an indicator variable that equals one for both treated and control analysts in the cohort starting in the first quarter when the treated analyst's city implements the monitoring program and remains one for all subsequent quarters. All variables are defined in the Variable Appendix in the paper or in Table Internet Appendix A. Standard errors are clustered at the City × Year level and reported in parentheses. *, **, *** indicate statistical significance at the 10%, 5%, and 1% levels (two-sided), respectively.

Table B8. Alternative proxy for air pollution discussion

The model estimated:

$$y_{i,j,q,c} = \beta\ Treated_{i,c} \times Post_{q,c} + \alpha_{j,q,c} + \alpha_{i,j,c} + \varepsilon_{i,j,q,c}$$

where, i, j, q, and c index analysts, firms, calendar year-quarters, and treatment cohorts, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
$y \Rightarrow$	*Air Pollution Discussed–Dict*					
Heterogeneity tests $\Rightarrow$	*Full Sample*	*LLM-based classification*			*Government-designated classification*	
		Green	*Neutral*	*Brown*	*Not Brown*	*Brown*
Treated × *Post*	0.030***	0.064*	0.019*	0.075***	0.007	0.163*
	(0.011)	(0.032)	(0.010)	(0.026)	(0.005)	(0.082)
p-value for $\beta_{Green} - \beta_{Neutral} > 0$			0.069			
p-value for $\beta_{Brown} - \beta_{Neutral} > 0$			0.004			
p-value for $\beta_{Green} - \beta_{Brown} > 0$			0.612			
p-value for $\beta_{Brown} - \beta_{Not\ Brown} > 0$					0.025	
Obs. (Analyst Report-Cohort Level)	67,389	7,353	52,876	7,160	55,182	12,207
Number of Unique Analysts	715	292	684	257	690	462
Number of Unique Firms	1,460	184	1,127	149	1,107	353
Firm × Year-Quarter × Cohort FE	Yes	Yes	Yes	Yes	Yes	Yes
Analyst × Firm × Cohort FE	Yes	Yes	Yes	Yes	Yes	Yes
Adj. R^2	39.5%	46.9%	34.4%	15.4%	42.6%	26.6%
Pre-program Mean of y	0.023	0.080	0.014	0.029	0.020	0.034
Pre-program Standard Deviation of y	0.148	0.272	0.116	0.168	0.140	0.180

Notes: This table reports results on the effect of the monitoring program using an alternative measure of analyst discussions of firms' activities in their reports. The dependent variable is *Air Pollution Discussed–Dict*, defined as an indicator variable that equals one if the analyst report contains air pollution-related words and phrases from a pollution dictionary developed by Lin et al. (2024). Column 1 reports evidence on the effects of the monitoring program on the alternative measure of analyst discussions of firms' activities in their reports using a stacked cohort DiD design. In Columns 2–4, we partition analyst reports into three groups: *Brown*, *Neutral*, and *Green*. We instruct *DeepSeek-Reasoner* to focus exclusively on the firm's business description in the MD&A section of the annual reports of 2011 and to classify a firm as *Brown* (*Green*) if its description indicates that the firm faces risks or costs (gains an advantage or opportunity) from heightened attention to air quality issues, as defined by the SASB. Firms not classified as *Brown* or *Green* are designated *Neutral*. We estimate separate regressions for each of these three groups. In Columns 5 and 6, we partition analyst reports in our sample into two groups based on whether the covered firm is included in the Environmental Survey and Reporting (ESR) database in 2011, the year before the implementation of the monitoring program. We estimate Equation 2 separately for analyst reports covering firms included in ESR (*Brown* firms) and those covering firms not included in ESR (*Not Brown* firms). *Treated* is an indicator variable that equals one for treated analysts in each cohort and zero for control analysts in the cohort. *Post* is an indicator variable that equals one for both treated and control analysts in the cohort starting in the first quarter when the treated analyst's city implements the monitoring program and remains one for all subsequent quarters. All variables are defined in the Variable Appendix in the paper or in Table Internet Appendix A. Standard errors are clustered at the City × Year level and reported in parentheses. *, **, *** indicate statistical significance at the 10%, 5%, and 1% levels (two-sided), respectively.

Table B9. Alternative specification for heterogeneity tests: Triple interaction

The model estimated in odd-numbered columns:

$$y_{i,j,q,c} = \beta\ \textit{Treated}_{i,c} \times \textit{Post}_{q,c} + \delta\ \textit{Treated}_{i,c} \times \textit{Post}_{q,c} \times \textit{Green-LLM classification}_{i,c} + \theta\ \textit{Treated}_{i,c} \times \textit{Post}_{q,c} \times \textit{Brown-LLM classification}_{i,c} + \alpha_{j,q,c} + \alpha_{i,j,c} + \varepsilon_{i,j,q,c}$$

The model estimated in even-numbered columns:

$$y_{i,j,q,c} = \beta\ \textit{Treated}_{i,c} \times \textit{Post}_{q,c} + \delta\ \textit{Treated}_{i,c} \times \textit{Post}_{q,c} \times \textit{Brown-Govt classification}_{i,c} + \alpha_{j,q,c} + \alpha_{i,j,c} + \varepsilon_{i,j,q,c}$$

where i, j, q, and c index analysts, firms, calendar year-quarters, and cohorts, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
$y \Rightarrow$	*Air Pollution Discussed*		*EPS Forecast (%)*		*Recommendation*		*Target Price*		*Report Tone*		*Market Reaction (%)*	
Treated×*Post*	0.013***	0.011***	0.042	0.040	0.002	0.021	0.007	0.027	−0.001	0.009	−0.119	0.077
	(0.002)	(0.003)	(0.032)	(0.025)	(0.018)	(0.017)	(0.036)	(0.042)	(0.012)	(0.009)	(0.216)	(0.198)
Treated×*Post*×*Green-LLM classification*	0.048**		0.243**		0.150***		0.130**		0.082***		0.983**	
	(0.020)		(0.101)		(0.047)		(0.054)		(0.027)		(0.401)	
Treated×*Post*×*Brown-LLM classification*	0.037**		−0.482***		−0.167***		−0.136**		−0.062***		−1.035***	
	(0.017)		(0.131)		(0.038)		(0.053)		(0.020)		(0.357)	
Treated×*Post*×*Brown-Govt classification*		0.073**		−0.166***		−0.146***		−0.174*		−0.052***		−1.448***
		(0.029)		(0.055)		(0.030)		(0.090)		(0.012)		(0.362)
Obs. (Analyst Report-Cohort Level)	67,389	67,389	67,071	67,071	65,389	65,389	21,705	21,705	67,389	67,389	56,688	56,688
Number of Unique Analysts	715	715	715	715	711	711	563	563	715	715	713	713
Number of Unique Firms	1,460	1,460	1,458	1,458	1,443	1,443	1,113	1,113	1,460	1,460	1,448	1,448
Firm × Year-Quarter × Cohort FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Analyst × Firm × Cohort FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adj. R^2	47.4%	47.5%	96.7%	96.6%	78.7%	78.6%	76.9%	76.9%	47.3%	47.3%	32.1%	32.1%
Pre-program Mean of y	0.021	0.021	4.612	4.612	4.331	4.331	1.241	1.241	−0.037	−0.037	0.975	0.975
Pre-program Standard Deviation of y	0.145	0.145	3.077	3.077	0.599	0.599	0.602	0.602	0.290	0.290	4.724	4.724

Table B9 (Continued)

Notes: This table reports the results on the heterogeneity of the effect of the monitoring program on analyst discussions of firms' air-polluting activities in their reports using an alternative specification. In odd-numbered columns, we estimate an augmented Equation 2 by adding the interaction term among *Green-LLM classification*, *Treat*, and *Post* as well as the interaction term among *Brown-LLM classification*, *Treat*, and *Post*. In even-numbered columns, we estimate an augmented Equation 2 by adding the interaction term among *Brown-Govt classification*, *Treat*, and *Post*. *Green-LLM classification* (*Brown-LLM classification*) is an indicator variable that equals one if the firm is a green (brown) firm. This variable is derived by instructing a generative large language model (*DeepSeek-Reasoner*) to focus exclusively on the firm's business description in the MD&A section of the annual reports of 2011 and to classify the firm as green if the description indicates that the firm gains an advantage or opportunity (faces risks or costs) from heightened attention to air quality issues, as defined by the Sustainability Accounting Standards Board (SASB). Firms not classified as Brown or Green are designated Neutral, which serves as our base group in even-numbered columns. *Brown-Govt classification* is an indicator variable that equals one if a firm is included in the Environmental Survey and Reporting (ESR) database in 2011, and zero otherwise. *Air Pollution Discussed* is an indicator variable that equals one if the analyst's report discusses air quality as defined by the SASB and measured using a large language model (*DeepSeek-R1*). *EPS Forecast* is defined as the analyst's EPS forecast, scaled by the firm's stock price at the beginning of the fiscal year, multiplied by 100. *Recommendation* is the analyst's stock recommendation, coded as an ordinal variable ranging from 1 to 5, where 5 indicates a Strong Buy and 1 indicates a Strong Sell. *Target Price* is the ratio of the analyst's target price to the firm's actual stock price at the beginning of the fiscal year. *Report Tone* is calculated as (Positive - Negative) / (Positive + Negative), where Negative (Positive) represents the word count frequency of negative (positive) words in the analyst report as obtained from the CNRDS dataset. Negative and positive words are identified using the Loughran-McDonald dictionary. *Market Reaction (%)* is the (signed) cumulative abnormal return over a three-day window centered on the analyst report date, multiplied by 100. *Treated* is an indicator variable that equals one for treated analysts in each cohort and zero for control analysts in the cohort. *Post* is an indicator variable that equals one for both treated and control analysts in the cohort starting in the first quarter when the treated analyst's city implements the monitoring program and remains one for all subsequent quarters. All variables are defined in the Variable Appendix in the paper or in Table Internet Appendix A. Standard errors are clustered at the City × Year level and reported in parentheses. *, **, *** indicate statistical significance at the 10%, 5%, and 1% levels (two-sided), respectively.

Table B10. Subsample limited to analysts located in cities different from the covered firm's city

The model estimated:

$$y_{i,j,q,c} = \beta \ Treated_{i,c} \times Post_{q,c} + \alpha_{j,q,c} + \alpha_{i,j,c} + \varepsilon_{i,j,q,c}$$

where, i, j, q, and c index analysts, firms, calendar year-quarters, and treatment cohorts, respectively.

Heterogeneity tests ⇒	(1) *Full Sample*	(2) *LLM-based classification*	(3)	(4)	(5) *Government-designated classification*	(6)
		Green	*Neutral*	*Brown*	*Not Brown*	*Brown*
y ⇒			*Air Pollution Discussed*			
Treated × *Post*	0.024***	0.068**	0.014***	0.055**	0.011***	0.093***
	(0.006)	(0.029)	(0.002)	(0.021)	(0.004)	(0.034)
p-value for $\beta_{Green} - \beta_{Neutral} > 0$			0.023			
p-value for $\beta_{Brown} - \beta_{Neutral} > 0$			0.022			
p-value for $\beta_{Green} - \beta_{Brown} > 0$			0.346			
p-value for $\beta_{Brown} - \beta_{Not\ Brown} > 0$					0.007	
Obs. (Analyst Report-Cohort Level)	59,992	6,761	46,925	6,306	48,584	11,408
Number of Unique Analysts	698	273	662	239	672	439
Number of Unique Firms	1,387	174	1,069	144	1,048	339
y ⇒			*EPS Forecast (%)*			
Treated × *Post*	0.030	0.276**	0.032	−0.232***	0.053	−0.105**
	(0.025)	(0.126)	(0.034)	(0.079)	(0.032)	(0.043)
p-value for $\beta_{Green} - \beta_{Neutral} > 0$			0.038			
p-value for $\beta_{Neutral} - \beta_{Brown} > 0$			0.002			
p-value for $\beta_{Green} - \beta_{Brown} > 0$			0.001			
p-value for $\beta_{Not\ Brown} - \beta_{Brown} > 0$					0.007	
Obs. (Analyst Report-Cohort Level)	59,703	6,723	46,713	6,267	48,375	11,328
Number of Unique Analysts	698	272	662	239	672	439
Number of Unique Firms	1,385	173	1,069	143	1,046	339
y ⇒			*Recommendation*			
Treated × *Post*	0.013	0.181**	0.020	−0.194***	0.040**	−0.132***
	(0.021)	(0.071)	(0.021)	(0.036)	(0.019)	(0.043)
p-value for $\beta_{Green} - \beta_{Neutral} > 0$			0.009			
p-value for $\beta_{Neutral} - \beta_{Brown} > 0$			0.000			
p-value for $\beta_{Green} - \beta_{Brown} > 0$			0.000			
p-value for $\beta_{Not\ Brown} - \beta_{Brown} > 0$					0.000	
Obs. (Analyst Report-Cohort Level)	58,150	6,537	45,398	6,215	47,201	10,949
Number of Unique Analysts	696	272	660	239	671	435
Number of Unique Firms	1,369	173	1,054	142	1,034	335

Table B10 (Continued)

Heterogeneity tests ⇒	(1) *Full Sample*	(2)	(3) *LLM-based classification*	(4)	(5)	(6) *Government-designated classification*
		Green	*Neutral*	*Brown*	*Not Brown*	*Brown*
y ⇒			*Target Price*			
Treated × *Post*	0.023	0.114*	0.026	−0.129***	0.046	−0.162**
	(0.042)	(0.057)	(0.046)	(0.037)	(0.053)	(0.067)
p-value for $\beta_{Green} - \beta_{Neutral} > 0$			0.113			
p-value for $\beta_{Neutral} - \beta_{Brown} > 0$			0.011			
p-value for $\beta_{Green} - \beta_{Brown} > 0$			0.000			
p-value for $\beta_{Not\ Brown} - \beta_{Brown} > 0$					0.027	
Obs. (Analyst Report-Cohort Level)	19,373	2,061	15,706	1,606	15,869	3,504
Number of Unique Analysts	546	183	499	159	515	291
Number of Unique Firms	1,052	126	820	106	804	248
y ⇒			*Report Tone*			
Treated × *Post*	0.003	0.066*	0.004	−0.062***	0.011	−0.038**
	(0.010)	(0.034)	(0.013)	(0.021)	(0.010)	(0.017)
p-value for $\beta_{Green} - \beta_{Neutral} > 0$			0.041			
p-value for $\beta_{Neutral} - \beta_{Brown} > 0$			0.010			
p-value for $\beta_{Green} - \beta_{Brown} > 0$			0.001			
p-value for $\beta_{Not\ Brown} - \beta_{Brown} > 0$					0.001	
Obs. (Analyst Report-Cohort Level)	59,992	6,761	46,925	6,306	48,584	11,408
Number of Unique Analysts	698	273	662	239	672	439
Number of Unique Firms	1,387	174	1,069	144	1,048	339
y ⇒			*Market Reaction (%)*			
Treated × *Post*	−0.188	0.851*	−0.182	−1.348***	0.048	−1.568***
	(0.174)	(0.429)	(0.186)	(0.416)	(0.184)	(0.440)
p-value for $\beta_{Green} - \beta_{Neutral} > 0$			0.008			
p-value for $\beta_{Neutral} - \beta_{Brown} > 0$			0.005			
p-value for $\beta_{Green} - \beta_{Brown} > 0$			0.000			
p-value for $\beta_{Not\ Brown} - \beta_{Brown} > 0$					0.000	
Obs. (Analyst Report-Cohort Level)	50,480	5,794	39,473	5,213	40,843	9,637
Number of Unique Analysts	696	272	660	237	671	438
Number of Unique Firms	1,377	174	1,061	142	1,042	335

Table B10 (Continued)

Notes: This table reports the results from replicating our main findings (i.e., Tables 4, 6, 7, and 9) using a subsample limited to analyst reports issued by analysts who reside in a different city from the covered firm's city. We examine six dependent variables, y, each reported in a separate table: *Air Pollution Discussed*, *EPS Forecast*, *Recommendation*, *Target Price*, *Report Tone*, and *Market Reaction (%)*. In each table, Column 1 reports the results from estimating Equation 2 using the full sample to explore the change in the dependent variable (y) for treated analysts from before to after the rollout of the monitoring program in their city, relative to control analysts. In Columns 2–4, we partition analyst reports into three groups: *Brown*, *Neutral*, and *Green*. We instruct *DeepSeek-Reasoner* to focus exclusively on the firm's business description in the MD&A section of the annual reports of 2011 and to classify a firm as *Brown* (*Green*) if its description indicates that the firm faces risks or costs (gains an advantage or opportunity) from heightened attention to air quality issues, as defined by the SASB. Firms not classified as *Brown* or *Green* are designated *Neutral*. We estimate Equation 2 separately for analyst reports covering firms in each of these three groups. In Columns 5 and 6, we partition analyst reports in our sample into two groups based on whether the covered firm is included in the Environmental Survey and Reporting (ESR) database in 2011, the year before the implementation of the monitoring program. We estimate Equation 2 separately for analyst reports covering firms included in ESR (*Brown* firms) and those covering firms not included in ESR (*Not Brown* firms). *Treated* is an indicator variable that equals one for treated analysts in each cohort and zero for control analysts in the cohort. *Post* is an indicator variable that equals one for both treated and control analysts in the cohort starting in the first quarter when the treated analyst's city implements the monitoring program and remains one for all subsequent quarters. *Air Pollution Discussed* is an indicator variable that equals one if the analyst's report discusses air quality as defined by the SASB and measured using a large language model (*DeepSeek-R1*). *EPS Forecast* is defined as the analyst's EPS forecast, scaled by the firm's stock price at the beginning of the fiscal year, multiplied by 100. *Recommendation* is the analyst's stock recommendation, coded as an ordinal variable ranging from 1 to 5, where 5 indicates a Strong Buy and 1 indicates a Strong Sell. *Target Price* is the ratio of the analyst's target price to the firm's actual stock price at the beginning of the fiscal year. *Report Tone* is calculated as (Positive - Negative) / (Positive + Negative), where Negative (Positive) represents the word count frequency of negative (positive) words in the analyst report as obtained from the CNRDS dataset. Negative and positive words are identified using the Loughran-McDonald dictionary. *Market Reaction (%)* is the (signed) cumulative abnormal return over a three-day window centered on the analyst report date, multiplied by 100. All variables are defined in the Variable Appendix in the paper. Standard errors are clustered at the City × Year level and reported in parentheses. *, **, *** indicate statistical significance at the 10%, 5%, and 1% levels (two-sided), respectively.

Table B11. Subsample limited to analyst reports issued for never-treated firms

The model estimated:

$$y_{i,j,q,c} = \beta \ Treated_{i,c} \times Post_{q,c} + \alpha_{j,q,c} + \alpha_{i,j,c} + \varepsilon_{i,j,q,c}$$

where, i, j, q, and c index analysts, firms, calendar year-quarters, and treatment cohorts, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
Heterogeneity tests ⇒	*Full Sample*	*LLM-based classification*			*Government-designated classification*	
		Green	*Neutral*	*Brown*	*Not Brown*	*Brown*
y ⇒			*Air Pollution Discussed*			
Treated × *Post*	0.032***	0.055	0.008	0.116***	−0.009	0.207***
	(0.006)	(0.059)	(0.008)	(0.022)	(0.009)	(0.053)
p-value for $\beta_{Green} - \beta_{Neutral} > 0$			0.204			
p-value for $\beta_{Brown} - \beta_{Neutral} > 0$			0.000			
p-value for $\beta_{Green} - \beta_{Brown} > 0$			0.843			
p-value for $\beta_{Brown} - \beta_{Not\ Brown} > 0$					0.000	
Obs. (Analyst Report-Cohort Level)	7,904	843	5,525	1,536	5,883	2,021
Number of Unique Analysts	339	79	287	90	264	173
Number of Unique Firms	168	24	117	27	98	70
y ⇒			*EPS Forecast (%)*			
Treated × *Post*	0.150	1.134**	0.134	−0.428**	0.200*	−0.095
	(0.092)	(0.454)	(0.098)	(0.195)	(0.110)	(0.178)
p-value for $\beta_{Green} - \beta_{Neutral} > 0$			0.010			
p-value for $\beta_{Neutral} - \beta_{Brown} > 0$			0.008			
p-value for $\beta_{Green} - \beta_{Brown} > 0$			0.002			
p-value for $\beta_{Not\ Brown} - \beta_{Brown} > 0$					0.091	
Obs. (Analyst Report–Cohort Level)	7,850	840	5,500	1,510	5,856	1,994
Number of Unique Analysts	339	79	287	90	264	173
Number of Unique Firms	167	24	117	26	97	70
y ⇒			*Recommendation*			
Treated × *Post*	0.017	0.396**	0.029	−0.256*	0.101**	−0.343***
	(0.044)	(0.149)	(0.034)	(0.136)	(0.043)	(0.117)
p-value for $\beta_{Green} - \beta_{Neutral} > 0$			0.004			
p-value for $\beta_{Neutral} - \beta_{Brown} > 0$			0.013			
p-value for $\beta_{Green} - \beta_{Brown} > 0$			0.001			
p-value for $\beta_{Not\ Brown} - \beta_{Brown} > 0$					0.000	
Obs. (Analyst Report–Cohort Level)	7,741	818	5,405	1,518	5,794	1,947
Number of Unique Analysts	338	79	286	90	263	173
Number of Unique Firms	167	24	117	26	97	70

Table B11 (Continued)

Heterogeneity tests ⇒	(1) *Full Sample*	(2) *LLM-based classification*	(3)	(4)	(5) *Government-designated classification*	(6)
		Green	*Neutral*	*Brown*	*Not Brown*	*Brown*
y ⇒			*Target Price*			
Treated × *Post*	−0.013	0.312***	−0.026	−0.389***	0.042	−0.194**
	(0.097)	(0.083)	(0.102)	(0.000)	(0.133)	(0.085)
p-value for $\beta_{Green} - \beta_{Neutral} > 0$			0.009			
p-value for $\beta_{Neutral} - \beta_{Brown} > 0$			0.001			
p-value for $\beta_{Green} - \beta_{Brown} > 0$		p-value not estimated (small N)				
p-value for $\beta_{Not\ Brown} - \beta_{Brown} > 0$					0.110	
Obs. (Analyst Report–Cohort Level)	2,286	242	1,717	327	1,726	560
Number of Unique Analysts	203	40	163	43	154	84
Number of Unique Firms	124	17	87	20	77	47
y ⇒			*Report Tone*			
Treated × *Post*	0.018	0.091	0.003	0.034	0.027	−0.021
	(0.020)	(0.065)	(0.027)	(0.044)	(0.019)	(0.040)
p-value for $\beta_{Green} - \beta_{Neutral} > 0$			0.104			
p-value for $\beta_{Neutral} - \beta_{Brown} > 0$			0.744			
p-value for $\beta_{Green} - \beta_{Brown} > 0$			0.272			
p-value for $\beta_{Not\ Brown} - \beta_{Brown} > 0$					0.084	
Obs. (Analyst Report–Cohort Level)	7,904	843	5,525	1,536	5,883	2,021
Number of Unique Analysts	339	79	287	90	264	173
Number of Unique Firms	168	24	117	27	98	70
y ⇒			*Market Reaction (%)*			
Treated × *Post*	0.241	1.146	0.238	−0.254	0.474	−0.702
	(0.448)	(1.559)	(0.547)	(1.058)	(0.479)	(0.573)
p-value for $\beta_{Green} - \beta_{Neutral} > 0$			0.253			
p-value for $\beta_{Neutral} - \beta_{Brown} > 0$			0.343			
p-value for $\beta_{Green} - \beta_{Brown} > 0$			0.240			
p-value for $\beta_{Not\ Brown} - \beta_{Brown} > 0$					0.025	
Obs. (Analyst Report-Cohort Level)	6,674	719	4,678	1,277	4,945	1,729
Number of Unique Analysts	337	79	284	90	264	171
Number of Unique Firms	166	24	115	27	98	68

Table B11 (Continued)

Notes: This table reports the results from replicating our main findings (i.e., Tables 4, 6, 7, and 9) using a subsample limited to analyst reports covering never-treated firms, defined as firms located in cities that implemented the monitoring program after the end of our sample period (2013Q3). We examine six dependent variables, y, each reported in a separate table: *Air Pollution Discussed*, *EPS Forecast*, *Recommendation*, *Target Price*, *Report Tone*, and *Market Reaction (%)*. In each table, Column 1 reports the results from estimating Equation 2 using the full sample to explore the change in the dependent variable (y) for treated analysts from before to after the rollout of the monitoring program in their city, relative to control analysts. In Columns 2–4, we partition analyst reports into three groups: *Brown*, *Neutral*, and *Green*. We instruct *DeepSeek-Reasoner* to focus exclusively on the firm's business description in the MD&A section of the annual reports of 2011 and to classify a firm as *Brown* (*Green*) if its description indicates that the firm faces risks or costs (gains an advantage or opportunity) from heightened attention to air quality issues, as defined by the SASB. Firms not classified as *Brown* or *Green* are designated *Neutral*. We estimate Equation 2 separately for analyst reports covering firms in each of these three groups. In Columns 5 and 6, we partition analyst reports in our sample into two groups based on whether the covered firm is included in the Environmental Survey and Reporting (ESR) database in 2011, the year before the implementation of the monitoring program. We estimate Equation 2 separately for analyst reports covering firms included in ESR (*Brown* firms) and those covering firms not included in ESR (*Not Brown* firms). *Treated* is an indicator variable that equals one for treated analysts in each cohort and zero for control analysts in the cohort. *Post* is an indicator variable that equals one for both treated and control analysts in the cohort starting in the first quarter when the treated analyst's city implements the monitoring program and remains one for all subsequent quarters. *Air Pollution Discussed* is an indicator variable that equals one if the analyst's report discusses air quality as defined by the SASB and measured using a large language model (*DeepSeek-R1*). *EPS Forecast* is defined as the analyst's EPS forecast, scaled by the firm's stock price at the beginning of the fiscal year, multiplied by 100. *Recommendation* is the analyst's stock recommendation, coded as an ordinal variable ranging from 1 to 5, where 5 indicates a Strong Buy and 1 indicates a Strong Sell. *Target Price* is the ratio of the analyst's target price to the firm's actual stock price at the beginning of the fiscal year. *Report Tone* is calculated as (Positive - Negative) / (Positive + Negative), where Negative (Positive) represents the word count frequency of negative (positive) words in the analyst report as obtained from the CNRDS dataset. Negative and positive words are identified using the Loughran-McDonald dictionary. *Market Reaction (%)* is the (signed) cumulative abnormal return over a three-day window centered on the analyst report date, multiplied by 100. All variables are defined in the Variable Appendix in the paper or in Table Internet Appendix A. Standard errors are clustered at the City × Year level and reported in parentheses. *, **, *** indicate statistical significance at the 10%, 5%, and 1% levels (two-sided), respectively.

Table B12. Excluding cohorts

The model estimated:

$$y_{i,j,q,c} = \beta \ Treated_{i,c} \times Post_{q,c} + \alpha_{j,q,c} + \alpha_{i,j,c} + \varepsilon_{i,j,q,c}$$

where, i, j, q, and c index analysts, firms, calendar year-quarters, and treatment cohorts, respectively.

Panel A. Excluding Cohort 2013Q1

	(1)	(2)	(3)	(4)	(5)	(6)
Heterogeneity tests ⇒	*Full Sample*	*LLM-based classification*			*Government-designated classification*	
		Green	*Neutral*	*Brown*	*Not Brown*	*Brown*
y ⇒			*Air Pollution Discussed*			
Treated × *Post*	0.022***	0.061**	0.013***	0.050***	0.011***	0.084***
	(0.005)	(0.023)	(0.002)	(0.018)	(0.003)	(0.031)
p-value for $\beta_{Green} - \beta_{Neutral} > 0$			0.010			
p-value for $\beta_{Brown} - \beta_{Neutral} > 0$			0.015			
p-value for $\beta_{Green} - \beta_{Brown} > 0$			0.349			
p-value for $\beta_{Brown} - \beta_{Not\ Brown} > 0$					0.008	
Obs. (Analyst Report–Cohort Level)	67,371	7,349	52,864	7,158	55,169	12,202
Number of Unique Analysts	715	292	684	257	690	462
Number of Unique Firms	1,460	184	1,127	149	1,107	353
y ⇒			*EPS Forecast (%)*			
Treated × *Post*	0.018	0.284***	0.042	−0.440***	0.040	−0.125***
	(0.021)	(0.096)	(0.031)	(0.114)	(0.025)	(0.044)
p-value for $\beta_{Green} - \beta_{Neutral} > 0$			0.010			
p-value for $\beta_{Neutral} - \beta_{Brown} > 0$			0.000			
p-value for $\beta_{Green} - \beta_{Brown} > 0$			0.000			
p-value for $\beta_{Not\ Brown} - \beta_{Brown} > 0$					0.002	
Obs. (Analyst Report–Cohort Level)	67,054	7,307	52,631	7,116	54,936	12,118
Number of Unique Analysts	715	291	684	257	690	462
Number of Unique Firms	1,458	183	1,127	148	1,105	353
y ⇒			*Recommendation*			
Treated × *Post*	0.000	0.152***	0.002	−0.165***	0.021	−0.125***
	(0.018)	(0.054)	(0.018)	(0.031)	(0.016)	(0.037)
p-value for $\beta_{Green} - \beta_{Neutral} > 0$			0.001			
p-value for $\beta_{Neutral} - \beta_{Brown} > 0$			0.000			
p-value for $\beta_{Green} - \beta_{Brown} > 0$			0.000			
p-value for $\beta_{Not\ Brown} - \beta_{Brown} > 0$					0.000	
Obs. (Analyst Report–Cohort Level)	65,372	7,106	51,206	7,060	53,651	11,721
Number of Unique Analysts	711	291	680	257	687	459
Number of Unique Firms	1,443	183	1,112	148	1,093	350

Table B12 (Continued)

Panel A. Excluding Cohort 2013Q1 (Continued)

Heterogeneity tests ⇒	(1) *Full Sample*	(2) *LLM-based classification*			(5) *Government-designated classification*	
		Green	*Neutral*	*Brown*	*Not Brown*	*Brown*
y ⇒			*Target Price*			
Treated × *Post*	0.008	0.137***	0.007	−0.129***	0.027	−0.147**
	(0.033)	(0.046)	(0.036)	(0.037)	(0.041)	(0.065)
p-value for $\beta_{Green} - \beta_{Neutral} > 0$			0.011			
p-value for $\beta_{Neutral} - \beta_{Brown} > 0$			0.007			
p-value for $\beta_{Green} - \beta_{Brown} > 0$			0.000			
p-value for $\beta_{Not\ Brown} - \beta_{Brown} > 0$					0.030	
Obs. (Analyst Report–Cohort Level)	21,694	2,265	17,626	1,803	17,951	3,743
Number of Unique Analysts	562	198	520	169	533	302
Number of Unique Firms	1,112	135	864	113	854	258
y ⇒			*Report Tone*			
Treated × *Post*	0.001	0.081***	−0.001	−0.063***	0.009	−0.043**
	(0.009)	(0.026)	(0.012)	(0.014)	(0.009)	(0.017)
p-value for $\beta_{Green} - \beta_{Neutral} > 0$			0.002			
p-value for $\beta_{Neutral} - \beta_{Brown} > 0$			0.001			
p-value for $\beta_{Green} - \beta_{Brown} > 0$			0.000			
p-value for $\beta_{Not\ Brown} - \beta_{Brown} > 0$					0.000	
Obs. (Analyst Report–Cohort Level)	67,371	7,349	52,864	7,158	55,169	12,202
Number of Unique Analysts	715	292	684	257	690	462
Number of Unique Firms	1,460	184	1,127	149	1,107	353
y ⇒			*Market Reaction (%)*			
Treated × *Post*	−0.119	0.864**	−0.119	−1.154***	0.077	−1.372***
	(0.187)	(0.391)	(0.214)	(0.306)	(0.195)	(0.407)
p-value for $\beta_{Green} - \beta_{Neutral} > 0$			0.009			
p-value for $\beta_{Neutral} - \beta_{Brown} > 0$			0.003			
p-value for $\beta_{Green} - \beta_{Brown} > 0$			0.000			
p-value for $\beta_{Not\ Brown} - \beta_{Brown} > 0$					0.000	
Obs. (Analyst Report-Cohort Level)	56,671	6,292	44,439	5,940	46,387	10,284
Number of Unique Analysts	713	291	681	255	689	460
Number of Unique Firms	1,448	184	1,117	147	1,100	348

Table B12 (Continued)

Panel B. Excluding Cohort 2012Q4

Heterogeneity tests ⇒	(1) *Full Sample*	(2) *LLM-based classification*	(3)	(4)	(5) *Government-designated classification*	(6)
		Green	*Neutral*	*Brown*	*Not Brown*	*Brown*
y ⇒			*Air Pollution Discussed*			
Treated × *Post*	0.022***	0.061**	0.013***	0.050***	0.011***	0.084***
	(0.005)	(0.023)	(0.002)	(0.017)	(0.003)	(0.031)
p-value for $\beta_{Green} - \beta_{Neutral} > 0$			0.010			
p-value for $\beta_{Brown} - \beta_{Neutral} > 0$			0.015			
p-value for $\beta_{Green} - \beta_{Brown} > 0$			0.348			
p-value for $\beta_{Brown} - \beta_{Not\ Brown} > 0$					0.008	
Obs. (Analyst Report–Cohort Level)	66,766	7,253	52,443	7,070	54,664	12,102
Number of Unique Analysts	715	292	684	257	690	462
Number of Unique Firms	1,460	184	1,127	149	1,107	353
y ⇒			*EPS Forecast (%)*			
Treated × *Post*	0.018	0.284***	0.042	−0.440***	0.040	−0.125***
	(0.021)	(0.095)	(0.031)	(0.114)	(0.025)	(0.044)
p-value for $\beta_{Green} - \beta_{Neutral} > 0$			0.010			
p-value for $\beta_{Neutral} - \beta_{Brown} > 0$			0.000			
p-value for $\beta_{Green} - \beta_{Brown} > 0$			0.000			
p-value for $\beta_{Not\ Brown} - \beta_{Brown} > 0$					0.002	
Obs. (Analyst Report–Cohort Level)	66,453	7,211	52,213	7,029	54,431	12,022
Number of Unique Analysts	715	291	684	257	690	462
Number of Unique Firms	1,458	183	1,127	148	1,105	353
y ⇒			*Recommendation*			
Treated × *Post*	0.000	0.152***	0.002	−0.165***	0.021	−0.125***
	(0.018)	(0.054)	(0.018)	(0.031)	(0.016)	(0.037)
p-value for $\beta_{Green} - \beta_{Neutral} > 0$			0.001			
p-value for $\beta_{Neutral} - \beta_{Brown} > 0$			0.000			
p-value for $\beta_{Green} - \beta_{Brown} > 0$			0.000			
p-value for $\beta_{Not\ Brown} - \beta_{Brown} > 0$					0.000	
Obs. (Analyst Report–Cohort Level)	64,774	7,013	50,790	6,971	53,151	11,623
Number of Unique Analysts	711	291	680	257	687	459
Number of Unique Firms	1,443	183	1,112	148	1,093	350

Table B12 (Continued)

Panel B. Excluding Cohort 2012Q4 (Continued)

Heterogeneity tests ⇒	(1) *Full Sample*	(2) *LLM-based classification*	(3)	(4)	(5) *Government-designated classification*	(6)
		Green	*Neutral*	*Brown*	*Not Brown*	*Brown*
y ⇒			*Target Price*			
Treated × *Post*	0.008	0.137***	0.007	−0.129***	0.027	−0.147**
	(0.033)	(0.046)	(0.036)	(0.037)	(0.041)	(0.065)
p-value for $\beta_{Green} - \beta_{Neutral} > 0$			0.011			
p-value for $\beta_{Neutral} - \beta_{Brown} > 0$			0.007			
p-value for $\beta_{Green} - \beta_{Brown} > 0$			0.000			
p-value for $\beta_{Not\ Brown} - \beta_{Brown} > 0$					0.030	
Obs. (Analyst Report–Cohort Level)	21,680	2,262	17,619	1,799	17,940	3,740
Number of Unique Analysts	562	198	520	169	534	301
Number of Unique Firms	1,113	135	864	114	855	258
y ⇒			*Report Tone*			
Treated × *Post*	0.001	0.081***	−0.001	−0.063***	0.009	−0.043**
	(0.009)	(0.026)	(0.012)	(0.014)	(0.009)	(0.017)
p-value for $\beta_{Green} - \beta_{Neutral} > 0$			0.002			
p-value for $\beta_{Neutral} - \beta_{Brown} > 0$			0.001			
p-value for $\beta_{Green} - \beta_{Brown} > 0$			0.000			
p-value for $\beta_{Not\ Brown} - \beta_{Brown} > 0$					0.000	
Obs. (Analyst Report–Cohort Level)	66,766	7,253	52,443	7,070	54,664	12,102
Number of Unique Analysts	715	292	684	257	690	462
Number of Unique Firms	1,460	184	1,127	149	1,107	353
y ⇒			*Market Reaction (%)*			
Treated × *Post*	−0.119	0.864**	−0.119	−1.154***	0.077	−1.372***
	(0.186)	(0.390)	(0.214)	(0.305)	(0.195)	(0.406)
p-value for $\beta_{Green} - \beta_{Neutral} > 0$			0.009			
p-value for $\beta_{Neutral} - \beta_{Brown} > 0$			0.003			
p-value for $\beta_{Green} - \beta_{Brown} > 0$			0.000			
p-value for $\beta_{Not\ Brown} - \beta_{Brown} > 0$					0.000	
Obs. (Analyst Report–Cohort Level)	56,165	6,208	44,092	5,865	45,961	10,204
Number of Unique Analysts	713	291	681	255	689	460
Number of Unique Firms	1,448	184	1,117	147	1,100	348

Table B12 (Continued)

Panel C. Excluding Cohort 2012Q3

Heterogeneity tests ⇒	(1) *Full Sample*	(2) *LLM-based classification*	(3)	(4)	(5) *Government-designated classification*	(6)
		Green	*Neutral*	*Brown*	*Not Brown*	*Brown*
y ⇒			*Air Pollution Discussed*			
Treated × *Post*	0.023***	0.066**	0.013***	0.052***	0.012***	0.090**
	(0.005)	(0.027)	(0.002)	(0.018)	(0.003)	(0.034)
p-value for $\beta_{Green} - \beta_{Neutral} > 0$			0.015			
p-value for $\beta_{Brown} - \beta_{Neutral} > 0$			0.017			
p-value for $\beta_{Green} - \beta_{Brown} > 0$			0.319			
p-value for $\beta_{Brown} - \beta_{Not\ Brown} > 0$					0.010	
Obs. (Analyst Report–Cohort Level)	46,287	5,042	36,268	4,977	37,919	8,368
Number of Unique Analysts	715	292	684	257	690	462
Number of Unique Firms	1,460	184	1,127	149	1,107	353
y ⇒			*EPS Forecast (%)*			
Treated × *Post*	0.019	0.292***	0.043	−0.435***	0.041	−0.128***
	(0.022)	(0.089)	(0.032)	(0.119)	(0.026)	(0.045)
p-value for $\beta_{Green} - \beta_{Neutral} > 0$			0.006			
p-value for $\beta_{Neutral} - \beta_{Brown} > 0$			0.001			
p-value for $\beta_{Green} - \beta_{Brown} > 0$			0.000			
p-value for $\beta_{Not\ Brown} - \beta_{Brown} > 0$					0.002	
Obs. (Analyst Report–Cohort Level)	46,052	5,010	36,094	4,948	37,750	8,302
Number of Unique Analysts	715	291	684	257	690	462
Number of Unique Firms	1,458	183	1,127	148	1,105	353
y ⇒			*Recommendation*			
Treated × *Post*	0.006	0.184***	0.006	−0.153***	0.028	−0.122***
	(0.020)	(0.047)	(0.020)	(0.033)	(0.018)	(0.042)
p-value for $\beta_{Green} - \beta_{Neutral} > 0$			0.000			
p-value for $\beta_{Neutral} - \beta_{Brown} > 0$			0.000			
p-value for $\beta_{Green} - \beta_{Brown} > 0$			0.000			
p-value for $\beta_{Not\ Brown} - \beta_{Brown} > 0$					0.000	
Obs. (Analyst Report–Cohort Level)	44,816	4,860	35,055	4,901	36,798	8,018
Number of Unique Analysts	711	289	680	257	687	457
Number of Unique Firms	1,408	178	1,082	148	1,062	346

Table B12 (Continued)

Panel C. Excluding Cohort 2012Q3 (Continued)

Heterogeneity tests ⇒	(1) *Full Sample*	(2) *LLM-based classification*	(3)	(4)	(5) *Government-designated classification*	(6)
		Green	*Neutral*	*Brown*	*Not Brown*	*Brown*
y ⇒			*Target Price*			
Treated × *Post*	0.008	0.137***	0.007	−0.129***	0.027	−0.147**
	(0.034)	(0.048)	(0.036)	(0.037)	(0.042)	(0.067)
p-value for $\beta_{Green} - \beta_{Neutral} > 0$			0.012			
p-value for $\beta_{Neutral} - \beta_{Brown} > 0$			0.008			
p-value for $\beta_{Green} - \beta_{Brown} > 0$			0.000			
p-value for $\beta_{Not\ Brown} - \beta_{Brown} > 0$					0.032	
Obs. (Analyst Report–Cohort Level)	15,500	1,619	12,525	1,356	12,866	2,634
Number of Unique Analysts	548	191	504	164	519	290
Number of Unique Firms	1,100	135	853	112	844	256
y ⇒			*Report Tone*			
Treated × *Post*	−0.001	0.075***	−0.002	−0.065***	0.007	−0.047**
	(0.009)	(0.022)	(0.012)	(0.015)	(0.009)	(0.019)
p-value for $\beta_{Green} - \beta_{Neutral} > 0$			0.002			
p-value for $\beta_{Neutral} - \beta_{Brown} > 0$			0.002			
p-value for $\beta_{Green} - \beta_{Brown} > 0$			0.000			
p-value for $\beta_{Not\ Brown} - \beta_{Brown} > 0$					0.000	
Obs. (Analyst Report–Cohort Level)	46,287	5,042	36,268	4,977	37,919	8,368
Number of Unique Analysts	715	292	684	257	690	462
Number of Unique Firms	1,460	184	1,127	149	1,107	353
y ⇒			*Market Reaction (%)*			
Treated × *Post*	−0.182	0.725**	−0.167	−1.155***	0.026	−1.551***
	(0.196)	(0.358)	(0.224)	(0.330)	(0.207)	(0.423)
p-value for $\beta_{Green} - \beta_{Neutral} > 0$			0.008			
p-value for $\beta_{Neutral} - \beta_{Brown} > 0$			0.005			
p-value for $\beta_{Green} - \beta_{Brown} > 0$			0.000			
p-value for $\beta_{Not\ Brown} - \beta_{Brown} > 0$					0.000	
Obs. (Analyst Report-Cohort Level)	38,561	4,291	30,180	4,090	31,596	6,965
Number of Unique Analysts	712	288	680	252	688	453
Number of Unique Firms	1,436	184	1,106	146	1,088	348

Table B12 (Continued)

Panel D. Excluding Cohort 2012Q2

Heterogeneity tests ⇒	(1) *Full Sample*	(2) *LLM-based classification*		(4)	(5) *Government-designated classification*	(6)
		Green	*Neutral*	*Brown*	*Not Brown*	*Brown*
y ⇒			*Air Pollution Discussed*			
Treated × *Post*	0.016***	0.024	0.011***	0.045***	0.010***	0.048***
	(0.003)	(0.016)	(0.002)	(0.015)	(0.003)	(0.016)
p-value for $\beta_{Green} - \beta_{Neutral} > 0$			0.200			
p-value for $\beta_{Brown} - \beta_{Neutral} > 0$			0.013			
p-value for $\beta_{Green} - \beta_{Brown} > 0$			0.812			
p-value for $\beta_{Brown} - \beta_{Not\ Brown} > 0$					0.014	
Obs. (Analyst Report–Cohort Level)	47,928	5,212	37,562	5,154	39,201	8,727
Number of Unique Analysts	715	292	684	257	690	462
Number of Unique Firms	1,460	184	1,127	149	1,107	353
y ⇒			*EPS Forecast (%)*			
Treated × *Post*	0.028	0.305***	0.057*	−0.463***	0.055**	−0.138***
	(0.022)	(0.104)	(0.029)	(0.100)	(0.022)	(0.043)
p-value for $\beta_{Green} - \beta_{Neutral} > 0$			0.017			
p-value for $\beta_{Neutral} - \beta_{Brown} > 0$			0.000			
p-value for $\beta_{Green} - \beta_{Brown} > 0$			0.000			
p-value for $\beta_{Not\ Brown} - \beta_{Brown} > 0$					0.000	
Obs. (Analyst Report–Cohort Level)	47,712	5,182	37,409	5,121	39,048	8,664
Number of Unique Analysts	715	291	684	257	690	462
Number of Unique Firms	1,457	182	1,127	148	1,104	353
y ⇒			*Recommendation*			
Treated × *Post*	−0.019	0.115**	−0.013	−0.189***	0.004	−0.153***
	(0.015)	(0.053)	(0.018)	(0.038)	(0.015)	(0.032)
p-value for $\beta_{Green} - \beta_{Neutral} > 0$			0.010			
p-value for $\beta_{Neutral} - \beta_{Brown} > 0$			0.000			
p-value for $\beta_{Green} - \beta_{Brown} > 0$			0.000			
p-value for $\beta_{Not\ Brown} - \beta_{Brown} > 0$					0.000	
Obs. (Analyst Report–Cohort Level)	46,552	5,051	36,411	5,090	38,158	8,394
Number of Unique Analysts	711	290	680	257	687	459
Number of Unique Firms	1,438	182	1,108	148	1,088	350

Table B12 (Continued)

Panel D. Excluding Cohort 2012Q2 (Continued)

Heterogeneity tests ⇒	(1) *Full Sample*	(2) *LLM-based classification*	(3)	(4)	(5) *Government-designated classification*	(6)
		Green	*Neutral*	*Brown*	*Not Brown*	*Brown*
y ⇒			*Target Price*			
Treated × *Post*	0.075	0.117**	0.085	−0.157***	0.127*	−0.230***
	(0.058)	(0.054)	(0.062)	(0.043)	(0.067)	(0.042)
p-value for $\beta_{Green} - \beta_{Neutral} > 0$			0.351			
p-value for $\beta_{Neutral} - \beta_{Brown} > 0$			0.000			
p-value for $\beta_{Green} - \beta_{Brown} > 0$			0.000			
p-value for $\beta_{Not\ Brown} - \beta_{Brown} > 0$					0.000	
Obs. (Analyst Report–Cohort Level)	14,672	1,525	11,862	1,285	12,080	2,592
Number of Unique Analysts	549	187	506	160	522	288
Number of Unique Firms	1,088	130	848	110	836	252
y ⇒			*Report Tone*			
Treated × *Post*	0.004	0.081**	0.005	−0.075***	0.009	−0.020
	(0.009)	(0.031)	(0.009)	(0.017)	(0.010)	(0.015)
p-value for $\beta_{Green} - \beta_{Neutral} > 0$			0.007			
p-value for $\beta_{Neutral} - \beta_{Brown} > 0$			0.000			
p-value for $\beta_{Green} - \beta_{Brown} > 0$			0.000			
p-value for $\beta_{Not\ Brown} - \beta_{Brown} > 0$					0.033	
Obs. (Analyst Report–Cohort Level)	47,928	5,212	37,562	5,154	39,201	8,727
Number of Unique Analysts	715	292	684	257	690	462
Number of Unique Firms	1,460	184	1,127	149	1,107	353
y ⇒			*Market Reaction (%)*			
Treated × *Post*	0.100	1.143***	0.104	−1.002***	0.349*	−1.415***
	(0.184)	(0.359)	(0.230)	(0.340)	(0.192)	(0.375)
p-value for $\beta_{Green} - \beta_{Neutral} > 0$			0.003			
p-value for $\beta_{Neutral} - \beta_{Brown} > 0$			0.014			
p-value for $\beta_{Green} - \beta_{Brown} > 0$			0.000			
p-value for $\beta_{Not\ Brown} - \beta_{Brown} > 0$					0.000	
Obs. (Analyst Report-Cohort Level)	40,392	4,463	31,646	4,283	33,029	7,363
Number of Unique Analysts	710	287	678	252	686	454
Number of Unique Firms	1,443	184	1,114	145	1,097	346

Table B12 (Continued)

Panel E. Excluding Cohort 2012Q1

Heterogeneity tests ⇒	(1) *Full Sample*	(2) *LLM-based classification*			(5) *Government-designated classification*	
		Green	*Neutral*	*Brown*	*Not Brown*	*Brown*
y ⇒			*Air Pollution Discussed*			
Treated × *Post*	0.033***	0.113***	0.016***	0.060	0.014*	0.153***
	(0.009)	(0.038)	(0.006)	(0.041)	(0.007)	(0.054)
p-value for $\beta_{Green} - \beta_{Neutral} > 0$			0.003			
p-value for $\beta_{Brown} - \beta_{Neutral} > 0$			0.118			
p-value for $\beta_{Green} - \beta_{Brown} > 0$			0.167			
p-value for $\beta_{Brown} - \beta_{Not\ Brown} > 0$					0.005	
Obs. (Analyst Report–Cohort Level)	41,204	4,556	32,367	4,281	33,775	7,429
Number of Unique Analysts	494	207	473	181	475	331
Number of Unique Firms	1,246	155	955	136	964	282
y ⇒			*EPS Forecast (%)*			
Treated × *Post*	−0.004	0.233	0.002	−0.399	0.006	−0.082
	(0.047)	(0.171)	(0.055)	(0.268)	(0.057)	(0.106)
p-value for $\beta_{Green} - \beta_{Neutral} > 0$			0.090			
p-value for $\beta_{Neutral} - \beta_{Brown} > 0$			0.083			
p-value for $\beta_{Green} - \beta_{Brown} > 0$			0.013			
p-value for $\beta_{Not\ Brown} - \beta_{Brown} > 0$					0.261	
Obs. (Analyst Report–Cohort Level)	41,013	4,534	32,221	4,258	33,631	7,382
Number of Unique Analysts	494	207	473	181	475	331
Number of Unique Firms	1,245	155	955	135	963	282
y ⇒			*Recommendation*			
Treated × *Post*	0.021	0.145	0.020	−0.141**	0.035	−0.068
	(0.030)	(0.108)	(0.031)	(0.062)	(0.027)	(0.067)
p-value for $\beta_{Green} - \beta_{Neutral} > 0$			0.079			
p-value for $\beta_{Neutral} - \beta_{Brown} > 0$			0.020			
p-value for $\beta_{Green} - \beta_{Brown} > 0$			0.015			
p-value for $\beta_{Not\ Brown} - \beta_{Brown} > 0$					0.027	
Obs. (Analyst Report–Cohort Level)	40,042	4,410	31,410	4,222	32,894	7,148
Number of Unique Analysts	492	207	471	181	474	328
Number of Unique Firms	1,229	155	939	135	949	280

Table B12 (Continued)

Panel E. Excluding Cohort 2012Q1 (Continued)

Heterogeneity tests ⇒	(1) *Full Sample*	(2) *LLM-based classification*	(3)	(4)	(5) *Government-designated classification*	(6)
		Green	*Neutral*	*Brown*	*Not Brown*	*Brown*
y ⇒			*Target Price*			
Treated × *Post*	−0.046	0.160**	−0.053	−0.087	−0.047	−0.028
	(0.033)	(0.064)	(0.033)	(0.066)	(0.034)	(0.043)
p-value for $\beta_{Green} - \beta_{Neutral} > 0$			0.000			
p-value for $\beta_{Neutral} - \beta_{Brown} > 0$			0.306			
p-value for $\beta_{Green} - \beta_{Brown} > 0$			0.016			
p-value for $\beta_{NotBrown} - \beta_{Brown} > 0$					0.671	
Obs. (Analyst Report–Cohort Level)	13,274	1,401	10,900	973	10,995	2,279
Number of Unique Analysts	393	141	363	122	372	214
Number of Unique Firms	981	123	756	102	766	215
y ⇒			*Report Tone*			
Treated × *Post*	0.000	0.096**	−0.013	−0.024	0.014	−0.085***
	(0.019)	(0.046)	(0.019)	(0.044)	(0.019)	(0.030)
p-value for $\beta_{Green} - \beta_{Neutral} > 0$			0.007			
p-value for $\beta_{Neutral} - \beta_{Brown} > 0$			0.405			
p-value for $\beta_{Green} - \beta_{Brown} > 0$			0.036			
p-value for $\beta_{Not\ Brown} - \beta_{Brown} > 0$					0.000	
Obs. (Analyst Report–Cohort Level)	41,204	4,556	32,367	4,281	33,775	7,429
Number of Unique Analysts	494	207	473	181	475	331
Number of Unique Firms	1,246	155	955	136	964	282
y ⇒			*Market Reaction (%)*			
Treated × *Post*	−0.348	0.716	−0.395	−1.444**	−0.271	−0.848
	(0.336)	(0.772)	(0.336)	(0.557)	(0.324)	(0.764)
p-value for $\beta_{Green} - \beta_{Neutral} > 0$			0.077			
p-value for $\beta_{Neutral} - \beta_{Brown} > 0$			0.021			
p-value for $\beta_{Green} - \beta_{Brown} > 0$			0.004			
p-value for $\beta_{Not\ Brown} - \beta_{Brown} > 0$					0.181	
Obs. (Analyst Report-Cohort Level)	34,963	3,930	27,443	3,590	28,627	6,336
Number of Unique Analysts	492	206	470	180	474	329
Number of Unique Firms	1,240	155	949	136	961	279

Table B12 (Continued)

Notes: This table reports the results after sequentially excluding one cohort at a time from the sample. Each Panel corresponds to a specification that omits one of the five cohorts. In Panel A, we exclude cohort 2013Q1. In Panel B, we exclude cohort 2012Q4. In Panel C, we exclude cohort 2012Q3. In Panel D, we exclude cohort 2012Q2. In Panel E, we exclude cohort 2012Q1. We examine six dependent variables, y, each reported in a separate table: *Air Pollution Discussed*, *EPS Forecast*, *Recommendation*, *Target Price*, *Report Tone*, and *Market Reaction (%)*. In each table, Column 1 reports the results from estimating Equation 2 using the full sample to explore the change in the dependent variable (y) for treated analysts from before to after the rollout of the monitoring program in their city, relative to control analysts. In Columns 2–4, we partition analyst reports into three groups: *Brown*, *Neutral*, and *Green*. We instruct *DeepSeek-Reasoner* to focus exclusively on the firm's business description in the MD&A section of the annual reports of 2011 and to classify a firm as *Brown* (*Green*) if its description indicates that the firm faces risks or costs (gains an advantage or opportunity) from heightened attention to air quality issues, as defined by the SASB. Firms not classified as *Brown* or *Green* are designated *Neutral*. We estimate Equation 2 separately for analyst reports covering firms in each of these three groups. In Columns 5 and 6, we partition analyst reports in our sample into two groups based on whether the covered firm is included in the Environmental Survey and Reporting (ESR) database in 2011, the year before the implementation of the monitoring program. We estimate Equation 2 separately for analyst reports covering firms included in ESR (*Brown* firms) and those covering firms not included in ESR (*Not Brown* firms). *Treated* is an indicator variable that equals one for treated analysts in each cohort and zero for control analysts in the cohort. *Post* is an indicator variable that equals one for both treated and control analysts in the cohort starting in the first quarter when the treated analyst's city implements the monitoring program and remains one for all subsequent quarters. *Air Pollution Discussed* is an indicator variable that equals one if the analyst's report discusses air quality as defined by the SASB and measured using a large language model (*DeepSeek-R1*). *EPS Forecast* is defined as the analyst's EPS forecast, scaled by the firm's stock price at the beginning of the fiscal year, multiplied by 100. *Recommendation* is the analyst's stock recommendation, coded as an ordinal variable ranging from 1 to 5, where 5 indicates a Strong Buy and 1 indicates a Strong Sell. *Target Price* is the ratio of the analyst's target price to the firm's actual stock price at the beginning of the fiscal year. *Report Tone* is calculated as (Positive - Negative) / (Positive + Negative), where Negative (Positive) represents the word count frequency of negative (positive) words in the analyst report as obtained from the CNRDS dataset. Negative and positive words are identified using the Loughran-McDonald dictionary. *Market Reaction (%)* is the (signed) cumulative abnormal return over a three-day window centered on the analyst report date, multiplied by 100. All variables are defined in the Variable Appendix in the paper. Standard errors are clustered at the City × Year level and reported in parentheses. *, **, *** indicate statistical significance at the 10%, 5%, and 1% levels (two-sided), respectively.

Table B13. Clustering standard errors at the city-level

The model estimated:

$$y_{i,j,q,c} = \beta \ Treated_{i,c} \times Post_{q,c} + \alpha_{j,q,c} + \alpha_{i,j,c} + \varepsilon_{i,j,q,c}$$

where, i, j, q, and c index analysts, firms, calendar year-quarters, and treatment cohorts, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
Heterogeneity tests ⇒	*Full Sample*	*LLM-based classification*			*Government-designated classification*	
		Green	*Neutral*	*Brown*	*Not Brown*	*Brown*
y ⇒			*Air Pollution Discussed*			
Treated × *Post*	0.022***	0.061**	0.013***	0.050***	0.011***	0.084***
	[0.000]	[0.014]	[0.000]	[0.008]	[0.000]	[0.001]
p-value for $\beta_{Green} - \beta_{Neutral} > 0$			0.017			
p-value for $\beta_{Brown} - \beta_{Neutral} > 0$			0.034			
p-value for $\beta_{Green} - \beta_{Brown} > 0$			0.363			
p-value for $\beta_{Brown} - \beta_{Not\ Brown} > 0$					0.011	
Obs. (Analyst Report–Cohort Level)	67,389	7,353	52,876	7,160	55,182	12,207
Number of Unique Analysts	715	292	684	257	690	462
Number of Unique Firms	1,460	184	1,127	149	1,107	353
y ⇒			*EPS Forecast (%)*			
Treated × *Post*	0.018	0.284***	0.042	−0.440***	0.040*	−0.125***
	[0.290]	[0.000]	[0.212]	[0.000]	[0.086]	[0.000]
p-value for $\beta_{Green} - \beta_{Neutral} > 0$			0.018			
p-value for $\beta_{Neutral} - \beta_{Brown} > 0$			0.002			
p-value for $\beta_{Green} - \beta_{Brown} > 0$			0.000			
p-value for $\beta_{Not\ Brown} - \beta_{Brown} > 0$					0.001	
Obs. (Analyst Report–Cohort Level)	67,071	7,311	52,642	7,118	54,949	12,122
Number of Unique Analysts	715	291	684	257	690	462
Number of Unique Firms	1,458	183	1,127	148	1,105	353
y ⇒			*Recommendation*			
Treated × *Post*	0.000	0.152***	0.002	−0.165***	0.021	−0.125***
	[0.991]	[0.000]	[0.871]	[0.000]	[0.194]	[0.000]
p-value for $\beta_{Green} - \beta_{Neutral} > 0$			0.002			
p-value for $\beta_{Neutral} - \beta_{Brown} > 0$			0.000			
p-value for $\beta_{Green} - \beta_{Brown} > 0$			0.000			
p-value for $\beta_{Not\ Brown} - \beta_{Brown} > 0$					0.000	
Obs. (Analyst Report–Cohort Level)	65,389	7,110	51,218	7,061	53,663	11,726
Number of Unique Analysts	711	291	680	257	687	459
Number of Unique Firms	1,443	183	1,112	148	1,093	350

Table B13 (Continued)

Heterogeneity tests ⇒	(1) *Full Sample*	(2) *LLM-based classification*			(5) *Government-designated classification*	
		Green	*Neutral*	*Brown*	*Not Brown*	*Brown*
y ⇒			*Target Price*			
Treated × *Post*	0.008	0.137***	0.007	−0.129*	0.027	−0.147**
	[0.772]	[0.000]	[0.832]	[0.054]	[0.548]	[0.024]
p-value for $\beta_{Green} - \beta_{Neutral} > 0$			0.003			
p-value for $\beta_{Neutral} - \beta_{Brown} > 0$			0.010			
p-value for $\beta_{Green} - \beta_{Brown} > 0$			0.000			
p-value for $\beta_{Not\ Brown} - \beta_{Brown} > 0$					0.060	
Obs. (Analyst Report–Cohort Level)	21,705	2,268	17,633	1,804	17,958	3,747
Number of Unique Analysts	563	198	520	170	534	302
Number of Unique Firms	1,113	135	864	114	855	258
y ⇒			*Report Tone*			
Treated × *Post*	0.001	0.081***	−0.001	−0.063***	0.009**	−0.043***
	[0.800]	[0.000]	[0.871]	[0.000]	[0.039]	[0.000]
p-value for $\beta_{Green} - \beta_{Neutral} > 0$			0.003			
p-value for $\beta_{Neutral} - \beta_{Brown} > 0$			0.001			
p-value for $\beta_{Green} - \beta_{Brown} > 0$			0.001			
p-value for $\beta_{Not\ Brown} - \beta_{Brown} > 0$					0.000	
Obs. (Analyst Report–Cohort Level)	67,389	7,353	52,876	7,160	55,182	12,207
Number of Unique Analysts	715	292	684	257	690	462
Number of Unique Firms	1,460	184	1,127	149	1,107	353
y ⇒			*Market Reaction (%)*			
Treated × *Post*	−0.119	0.864***	−0.119	−1.154***	0.077	−1.372***
	[0.373]	[0.000]	[0.394]	[0.000]	[0.625]	[0.000]
p-value for $\beta_{Green} - \beta_{Neutral} > 0$			0.003			
p-value for $\beta_{Neutral} - \beta_{Brown} > 0$			0.001			
p-value for $\beta_{Green} - \beta_{Brown} > 0$			0.000			
p-value for $\beta_{Not\ Brown} - \beta_{Brown} > 0$					0.000	
Obs. (Analyst Report–Cohort Level)	56,688	6,296	44,450	5,942	46,400	10,288
Number of Unique Analysts	713	291	681	255	689	460
Number of Unique Firms	1,448	184	1,117	147	1,100	348

Table B13 (Continued)

Notes: This table reports the results from replicating our main findings (i.e., Tables 4, 6, 7, and 9) with standard errors clustered at the city level. Wild bootstrap p-values are reported in square brackets. Bootstrap p-values are computed using Webb weights with 999 replications. Following Davidson and MacKinnon (2004), the number of replications is chosen so that the significance level times the sum of the number of replications plus one is an integer. We examine six dependent variables, y, each reported in a separate table: *Air Pollution Discussed*, *EPS Forecast*, *Recommendation*, *Target Price*, *Report Tone*, and *Market Reaction (%)*. In each table, Column 1 reports the results from estimating Equation 2 using the full sample to explore the change in the dependent variable (y) for treated analysts from before to after the rollout of the monitoring program in their city, relative to control analysts. In Columns 2–4, we partition analyst reports into three groups: *Brown*, *Neutral*, and *Green*. We instruct *DeepSeek-Reasoner* to focus exclusively on the firm's business description in the MD&A section of the annual reports of 2011 and to classify a firm as *Brown* (*Green*) if its description indicates that the firm faces risks or costs (gains an advantage or opportunity) from heightened attention to air quality issues, as defined by the SASB. Firms not classified as *Brown* or *Green* are designated *Neutral*. We estimate Equation 2 separately for analyst reports covering firms in each of these three groups. In Columns 5 and 6, we partition analyst reports in our sample into two groups based on whether the covered firm is included in the Environmental Survey and Reporting (ESR) database in 2011, the year before the implementation of the monitoring program. We estimate Equation 2 separately for analyst reports covering firms included in ESR (*Brown* firms) and those covering firms not included in ESR (*Not Brown* firms). *Treated* is an indicator variable that equals one for treated analysts in each cohort and zero for control analysts in the cohort. *Post* is an indicator variable that equals one for both treated and control analysts in the cohort starting in the first quarter when the treated analyst's city implements the monitoring program and remains one for all subsequent quarters. *Air Pollution Discussed* is an indicator variable that equals one if the analyst's report discusses air quality as defined by the SASB and measured using a large language model (*DeepSeek-R1*). *EPS Forecast* is defined as the analyst's EPS forecast, scaled by the firm's stock price at the beginning of the fiscal year, multiplied by 100. *Recommendation* is the analyst's stock recommendation, coded as an ordinal variable ranging from 1 to 5, where 5 indicates a Strong Buy and 1 indicates a Strong Sell. *Target Price* is the ratio of the analyst's target price to the firm's actual stock price at the beginning of the fiscal year. *Report Tone* is calculated as (Positive - Negative) / (Positive + Negative), where Negative (Positive) represents the word count frequency of negative (positive) words in the analyst report as obtained from the CNRDS dataset. Negative and positive words are identified using the Loughran-McDonald dictionary. *Market Reaction (%)* is the (signed) cumulative abnormal return over a three-day window centered on the analyst report date, multiplied by 100. All variables are defined in the Variable Appendix. Wild bootstrap p-values are reported in square brackets. *, **, *** indicate statistical significance at the 10%, 5%, and 1% levels (two-sided), respectively.

Table B14. Including control variables

The model estimated:

$$y_{i,j,q,c} = \beta\ Treated_{i,c} \times Post_{q,c} + \gamma\ Controls + \alpha_{j,q,c} + \alpha_{i,j,c} + \varepsilon_{i,j,q,c}$$

where, i, j, q, and c index analysts, firms, calendar year-quarters, and treatment cohorts, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
Heterogeneity tests ⇒	*Full Sample*	*LLM-based classification*			*Government-designated classification*	
		Green	*Neutral*	*Brown*	*Not Brown*	*Brown*
y ⇒			*Air Pollution Discussed*			
Treated × *Post*	0.023***	0.060**	0.014***	0.056***	0.012***	0.085***
	(0.005)	(0.024)	(0.002)	(0.017)	(0.004)	(0.031)
Following History	−0.010*	−0.011	−0.007**	−0.032***	−0.009	−0.015
	(0.006)	(0.039)	(0.003)	(0.011)	(0.006)	(0.012)
Experience	0.013***	0.076	0.005	0.017	0.012**	0.016
	(0.004)	(0.053)	(0.005)	(0.051)	(0.005)	(0.031)
p-value for $\beta_{Green} - \beta_{Neutral} > 0$			0.017			
p-value for $\beta_{Brown} - \beta_{Neutral} > 0$			0.006			
p-value for $\beta_{Green} - \beta_{Brown} > 0$			0.445			
p-value for $\beta_{Brown} - \beta_{Not\ Brown} > 0$					0.009	
Obs. (Analyst Report–Cohort Level)	67,389	7,353	52,876	7,160	55,182	12,207
Number of Unique Analysts	715	292	684	257	690	462
Number of Unique Firms	1,460	184	1,127	149	1,107	353
y ⇒			*EPS Forecast (%)*			
Treated × *Post*	0.020	0.265***	0.047	−0.450***	0.043*	−0.127***
	(0.021)	(0.094)	(0.032)	(0.125)	(0.025)	(0.045)
Following History	−0.003	0.170**	−0.032	0.059	−0.010	0.034
	(0.038)	(0.068)	(0.034)	(0.110)	(0.044)	(0.050)
Experience	−0.043*	−0.055	−0.036	−0.103	−0.045*	−0.019
	(0.024)	(0.095)	(0.030)	(0.285)	(0.025)	(0.145)
p-value for $\beta_{Green} - \beta_{Neutral} > 0$			0.017			
p-value for $\beta_{Neutral} - \beta_{Brown} > 0$			0.001			
p-value for $\beta_{Green} - \beta_{Brown} > 0$			0.000			
p-value for $\beta_{Not\ Brown} - \beta_{Brown} > 0$					0.002	
Obs. (Analyst Report–Cohort Level)	67,071	7,311	52,642	7,118	54,949	12,122
Number of Unique Analysts	715	291	684	257	690	462
Number of Unique Firms	1,458	183	1,127	148	1,105	353

Table B14 (Continued)

Heterogeneity tests ⇒	(1) *Full Sample*	(2) *LLM-based classification*	(3)	(4)	(5) *Government-designated classification*	(6)
		Green	*Neutral*	*Brown*	*Not Brown*	*Brown*
y ⇒			*Recommendation*			
Treated × *Post*	−0.005	0.144**	−0.002	−0.166***	0.018	−0.136***
	(0.019)	(0.055)	(0.019)	(0.037)	(0.017)	(0.039)
Following History	0.035*	0.079	0.034*	0.010	0.022	0.102***
	(0.018)	(0.077)	(0.019)	(0.071)	(0.020)	(0.037)
Experience	−0.019	−0.046	−0.020	0.005	−0.021	0.006
	(0.027)	(0.106)	(0.028)	(0.055)	(0.028)	(0.067)
p-value for $\beta_{Green} - \beta_{Neutral} > 0$			0.002			
p-value for $\beta_{Neutral} - \beta_{Brown} > 0$			0.000			
p-value for $\beta_{Green} - \beta_{Brown} > 0$			0.000			
p-value for $\beta_{Not\ Brown} - \beta_{Brown} > 0$					0.000	
Obs. (Analyst Report–Cohort Level)	65,389	7,110	51,218	7,061	53,663	11,726
Number of Unique Analysts	711	291	680	257	687	459
Number of Unique Firms	1,443	183	1,112	148	1,093	350
y ⇒			*Target Price*			
Treated × *Post*	0.002	0.095	−0.002	−0.126**	0.020	−0.142*
	(0.034)	(0.082)	(0.037)	(0.050)	(0.043)	(0.070)
Following History	0.063	−0.146	0.086	0.010	0.063	0.046
	(0.047)	(0.119)	(0.057)	(0.124)	(0.043)	(0.161)
Experience	−0.028	−0.057	−0.040	0.103	−0.034	0.048
	(0.095)	(0.088)	(0.121)	(0.179)	(0.086)	(0.264)
p-value for $\beta_{Green} - \beta_{Neutral} > 0$			0.098			
p-value for $\beta_{Neutral} - \beta_{Brown} > 0$			0.018			
p-value for $\beta_{Green} - \beta_{Brown} > 0$			0.003			
p-value for $\beta_{Not\ Brown} - \beta_{Brown} > 0$					0.048	
Obs. (Analyst Report–Cohort Level)	21,705	2,268	17,633	1,804	17,958	3,747
Number of Unique Analysts	563	198	520	170	534	302
Number of Unique Firms	1,113	135	864	114	855	258

Table B14 (Continued)

Heterogeneity tests ⇒	(1) *Full Sample*	(2) *LLM-based classification*	(3)	(4)	(5) *Government-designated classification*	(6)
		Green	*Neutral*	*Brown*	*Not Brown*	*Brown*
y ⇒			*Report Tone*			
Treated × *Post*	−0.003	0.077***	−0.005	−0.066***	0.004	−0.043**
	(0.010)	(0.027)	(0.013)	(0.014)	(0.010)	(0.017)
Following History	0.031*	0.031	0.033	0.019	0.035**	0.010
	(0.017)	(0.042)	(0.021)	(0.021)	(0.016)	(0.031)
Experience	−0.009	0.034	−0.019	0.041	−0.005	−0.038
	(0.012)	(0.047)	(0.012)	(0.034)	(0.012)	(0.027)
p-value for $\beta_{Green} - \beta_{Neutral} > 0$			0.005			
p-value for $\beta_{Neutral} - \beta_{Brown} > 0$			0.002			
p-value for $\beta_{Green} - \beta_{Brown} > 0$			0.000			
p-value for $\beta_{Not\ Brown} - \beta_{Brown} > 0$					0.001	
Obs. (Analyst Report–Cohort Level)	67,389	7,353	52,876	7,160	55,182	12,207
Number of Unique Analysts	715	292	684	257	690	462
Number of Unique Firms	1,460	184	1,127	149	1,107	353
y ⇒			*Market Reaction (%)*			
Treated × *Post*	−0.135	0.849**	−0.126	−1.247***	0.061	−1.380***
	(0.186)	(0.387)	(0.217)	(0.410)	(0.191)	(0.422)
Following History	0.119	0.151	0.085	0.297	0.130	0.041
	(0.143)	(0.357)	(0.158)	(0.829)	(0.164)	(0.373)
Experience	0.048	0.718	−0.095	0.938	−0.014	0.496
	(0.152)	(0.704)	(0.210)	(0.873)	(0.152)	(0.333)
p-value for $\beta_{Green} - \beta_{Neutral} > 0$			0.008			
p-value for $\beta_{Neutral} - \beta_{Brown} > 0$			0.009			
p-value for $\beta_{Green} - \beta_{Brown} > 0$			0.000			
p-value for $\beta_{Not\ Brown} - \beta_{Brown} > 0$					0.000	
Obs. (Analyst Report-Cohort Level)	56,688	6,296	44,450	5,942	46,400	10,288
Number of Unique Analysts	713	291	681	255	689	460
Number of Unique Firms	1,448	184	1,117	147	1,100	348

Table B14 (Continued)

Notes: This table reports the results from replicating our main findings (i.e., Tables 4, 6, 7, and 9) after adding control variables. *Controls* is a vector of control variables, including *Following History* and *Experience*. *Following History* is the natural logarithm of one plus the length of time (in quarters) that the analyst has been following the firm. *Experience* is the natural logarithm of one plus the number of quarters since the analyst issued their first report in the CNRDS dataset. We examine six dependent variables, y, each reported in a separate table: *Air Pollution Discussed*, *EPS Forecast*, *Recommendation*, *Target Price*, *Report Tone*, and *Market Reaction (%)*. In each table, Column 1 reports the results from estimating Equation 2 using the full sample to explore the change in the dependent variable (y) for treated analysts from before to after the rollout of the monitoring program in their city, relative to control analysts. In Columns 2–4, we partition analyst reports into three groups: *Brown*, *Neutral*, and *Green*. We instruct *DeepSeek-Reasoner* to focus exclusively on the firm's business description in the MD&A section of the annual reports of 2011 and to classify a firm as *Brown* (*Green*) if its description indicates that the firm faces risks or costs (gains an advantage or opportunity) from heightened attention to air quality issues, as defined by the SASB. Firms not classified as *Brown* or *Green* are designated *Neutral*. We estimate Equation 2 separately for analyst reports covering firms in each of these three groups. In Columns 5 and 6, we partition analyst reports in our sample into two groups based on whether the covered firm is included in the Environmental Survey and Reporting (ESR) database in 2011, the year before the implementation of the monitoring program. We estimate Equation 2 separately for analyst reports covering firms included in ESR (*Brown* firms) and those covering firms not included in ESR (*Not Brown* firms). *Treated* is an indicator variable that equals one for treated analysts in each cohort and zero for control analysts in the cohort. *Post* is an indicator variable that equals one for both treated and control analysts in the cohort starting in the first quarter when the treated analyst's city implements the monitoring program and remains one for all subsequent quarters. *Air Pollution Discussed* is an indicator variable that equals one if the analyst's report discusses air quality as defined by the SASB and measured using a large language model (*DeepSeek-R1*). *EPS Forecast* is defined as the analyst's EPS forecast, scaled by the firm's stock price at the beginning of the fiscal year, multiplied by 100. *Recommendation* is the analyst's stock recommendation, coded as an ordinal variable ranging from 1 to 5, where 5 indicates a Strong Buy and 1 indicates a Strong Sell. *Target Price* is the ratio of the analyst's target price to the firm's actual stock price at the beginning of the fiscal year. *Report Tone* is calculated as (Positive - Negative) / (Positive + Negative), where Negative (Positive) represents the word count frequency of negative (positive) words in the analyst report as obtained from the CNRDS dataset. Negative and positive words are identified using the Loughran-McDonald dictionary. *Market Reaction (%)* is the (signed) cumulative abnormal return over a three-day window centered on the analyst report date, multiplied by 100. All variables are defined in the Variable Appendix in the paper. Standard errors are clustered at the City × Year level and reported in parentheses. *, **, *** indicate statistical significance at the 10%, 5%, and 1% levels (two-sided), respectively.

Table B15. Staggered DiD design

The model estimated:

$$y_{i,j,q} = \beta \; Post \; Staggered_{i,q} + \alpha_{j,q} + \alpha_{i,j} + \varepsilon_{i,j,q}$$

where, i, j, and q index analysts, firms, and calendar year-quarters, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
Heterogeneity tests ⇒	*Full Sample*	*LLM-based classification*			*Government-designated classification*	
		Green	*Neutral*	*Brown*	*Not Brown*	*Brown*
y ⇒			*Air Pollution Discussed*			
Post Staggered	0.022**	0.040	0.015***	0.051**	0.010*	0.088**
	(0.008)	(0.035)	(0.005)	(0.022)	(0.006)	(0.037)
p-value for $\beta_{Green} - \beta_{Neutral} > 0$			0.205			
p-value for $\beta_{Brown} - \beta_{Neutral} > 0$			0.041			
p-value for $\beta_{Green} - \beta_{Brown} > 0$			0.615			
p-value for $\beta_{Brown} - \beta_{Not\ Brown} > 0$					0.008	
Obs. (Analyst Report Level)	50,405	5,466	39,738	5,201	41,533	8,872
Number of Unique Analysts	715	292	684	257	690	462
Number of Unique Firms	1,460	184	1,127	149	1,107	353
y ⇒			*EPS Forecast (%)*			
Post Staggered	0.028**	0.274***	0.038**	−0.295***	0.036**	−0.018
	(0.013)	(0.090)	(0.014)	(0.070)	(0.016)	(0.048)
p-value for $\beta_{Green} - \beta_{Neutral} > 0$			0.007			
p-value for $\beta_{Neutral} - \beta_{Brown} > 0$			0.000			
p-value for $\beta_{Green} - \beta_{Brown} > 0$			0.000			
p-value for $\beta_{Not\ Brown} - \beta_{Brown} > 0$					0.154	
Obs. (Analyst Report Level)	50,192	5,441	39,580	5,171	41,369	8,823
Number of Unique Analysts	715	292	684	257	690	462
Number of Unique Firms	1,460	184	1,127	149	1,107	353
y ⇒			*Recommendation*			
Post Staggered	−0.015	0.051	−0.016*	−0.074**	0.001	−0.110***
	(0.010)	(0.053)	(0.010)	(0.034)	(0.011)	(0.030)
p-value for $\beta_{Green} - \beta_{Neutral} > 0$			0.092			
p-value for $\beta_{Neutral} - \beta_{Brown} > 0$			0.065			
p-value for $\beta_{Green} - \beta_{Brown} > 0$			0.024			
p-value for $\beta_{Not\ Brown} - \beta_{Brown} > 0$					0.001	
Obs. (Analyst Report Level)	49,473	5,363	38,959	5,151	40,813	8,660
Number of Unique Analysts	715	292	684	257	690	462
Number of Unique Firms	1,458	184	1,125	149	1,105	353

Table B15 (Continued)

Heterogeneity tests ⇒	(1) *Full Sample*	(2) *LLM-based classification*	(3)	(4)	(5) *Government-designated classification*	(6)
		Green	*Neutral*	*Brown*	*Not Brown*	*Brown*
y ⇒			*Target Price*			
Post Staggered	−0.029	−0.142	0.000	−0.415	−0.050	0.140
	(0.061)	(0.258)	(0.045)	(0.705)	(0.066)	(0.120)
p-value for $\beta_{Green} - \beta_{Neutral} > 0$			0.711			
p-value for $\beta_{Neutral} - \beta_{Brown} > 0$			0.265			
p-value for $\beta_{Green} - \beta_{Brown} > 0$			0.345			
p-value for $\beta_{NotBrown} - \beta_{Brown} > 0$					0.921	
Obs. (Analyst Report Level)	15,934	1,780	12,765	1,389	13,287	2,647
Number of Unique Analysts	575	206	529	178	547	313
Number of Unique Firms	1,145	139	890	116	882	263
y ⇒			*Report Tone*			
Post Staggered	0.011*	0.044**	0.006	0.013	0.011*	0.012
	(0.006)	(0.017)	(0.007)	(0.019)	(0.006)	(0.016)
p-value for $\beta_{Green} - \beta_{Neutral} > 0$			0.014			
p-value for $\beta_{Neutral} - \beta_{Brown} > 0$			0.636			
p-value for $\beta_{Green} - \beta_{Brown} > 0$			0.148			
p-value for $\beta_{Not\ Brown} - \beta_{Brown} > 0$					0.549	
Obs. (Analyst Report Level)	50,405	5,466	39,738	5,201	41,533	8,872
Number of Unique Analysts	715	292	684	257	690	462
Number of Unique Firms	1,460	184	1,127	149	1,107	353
y ⇒			*Market Reaction (%)*			
Post Staggered	−0.082	0.909***	−0.106	−0.869***	0.100	−1.163***
	(0.147)	(0.284)	(0.156)	(0.223)	(0.155)	(0.311)
p-value for $\beta_{Green} - \beta_{Neutral} > 0$			0.000			
p-value for $\beta_{Neutral} - \beta_{Brown} > 0$			0.001			
p-value for $\beta_{Green} - \beta_{Brown} > 0$			0.000			
p-value for $\beta_{Not\ Brown} - \beta_{Brown} > 0$					0.000	
Obs. (Analyst Report-Cohort Level)	43,213	4,748	34,065	4,400	35,604	7,609
Number of Unique Analysts	714	292	683	256	690	461
Number of Unique Firms	1,452	184	1,121	147	1,101	351

Table B15 (Continued)

Notes: This table reports the results from replicating our main findings (i.e., Tables 4, 6, 7, and 9) using an alternative research design: a staggered DiD regression. *Post Staggered* is an indicator variable that equals one starting from the first quarter in which the monitoring program is implemented in the city where the analyst resides and remains one for all subsequent quarters. We examine six dependent variables, y, each reported in a separate table: *Air Pollution Discussed*, *EPS Forecast*, *Recommendation*, *Target Price*, *Report Tone*, and *Market Reaction (%)*. In each table, Column 1 reports the results using the full sample to explore the change in the dependent variable (y) for treated analysts from before to after the rollout of the monitoring program in their city, relative to control analysts. In Columns 2–4, we partition analyst reports into three groups: *Brown*, *Neutral*, and *Green*. We instruct *DeepSeek-Reasoner* to focus exclusively on the firm's business description in the MD&A section of the annual reports of 2011 and to classify a firm as *Brown* (*Green*) if its description indicates that the firm faces risks or costs (gains an advantage or opportunity) from heightened attention to air quality issues, as defined by the SASB. Firms not classified as *Brown* or *Green* are designated *Neutral*. We estimate separate regressions for analyst reports covering firms in each of these three groups. In Columns 5 and 6, we partition analyst reports in our sample into two groups based on whether the covered firm is included in the Environmental Survey and Reporting (ESR) database in 2011, the year before the implementation of the monitoring program. We estimate separate regressions for analyst reports covering firms included in ESR (*Brown* firms) and those covering firms not included in ESR (*Not Brown* firms). *Air Pollution Discussed* is an indicator variable that equals one if the analyst's report discusses air quality as defined by the SASB and measured using a large language model (*DeepSeek-R1*). *EPS Forecast* is defined as the analyst's EPS forecast, scaled by the firm's stock price at the beginning of the fiscal year, multiplied by 100. *Recommendation* is the analyst's stock recommendation, coded as an ordinal variable ranging from 1 to 5, where 5 indicates a Strong Buy and 1 indicates a Strong Sell. *Target Price* is the ratio of the analyst's target price to the firm's actual stock price at the beginning of the fiscal year. *Report Tone* is calculated as (Positive - Negative) / (Positive + Negative), where Negative (Positive) represents the word count frequency of negative (positive) words in the analyst report as obtained from the CNRDS dataset. Negative and positive words are identified using the Loughran-McDonald dictionary. *Market Reaction (%)* is the (signed) cumulative abnormal return over a three-day window centered on the analyst report date, multiplied by 100. All variables are defined in the Variable Appendix in the paper. Standard errors are clustered at the City × Year level and reported in parentheses. *, **, *** indicate statistical significance at the 10%, 5%, and 1% levels (two-sided), respectively.

Table B16. Distance between the analyst's city and the covered firm's city

The model estimated

$$y_{i,j,q,c} = \beta \ Treated_{i,c} \times Post_{q,c} + \alpha_{j,q,c} + \alpha_{i,j,c} + \varepsilon_{i,j,q,c}$$

where, i, j, q, and c index analysts, firms, calendar year-quarters, and treatment cohorts, respectively.

	(1)	(2)
$y \Rightarrow$	*Air Pollution Discussed*	
Above-Median Firm-Analyst Distance $\Rightarrow$	*No*	*Yes*
Treated × *Post*	0.020*	0.010***
	(0.010)	(0.003)
p-value for $\beta_{Yes} - \beta_{No} = 0$	0.610	
Observations (Analyst Report-Cohort Level)	35,369	32,020
Number of Unique Analysts	656	621
Number of Unique Firms	1,073	1,056
Firm × Year-Quarter × Cohort FE	Yes	Yes
Analyst × Firm × Cohort FE	Yes	Yes
Adj. R^2	45.9%	50.6%
Pre-program Mean of y	0.026	0.017
Pre-program Standard Deviation of y	0.159	0.128

Notes: This table reports results on whether the effect of the monitoring program on analyst discussions of firms' air-pollution activities in their reports varies with the distance between the analyst's city and the covered firm's city. We partition analyst reports in our sample into two groups based on whether the distance between the analyst's city and the covered firm's city is above the sample median, and estimate Equation 2 separately for these groups. *Air Pollution Discussed* is an indicator variable that equals one if the analyst's report discusses air quality as defined by the SASB and measured using a large language model (*DeepSeek-R1*). *Treated* is an indicator variable that equals one for treated analysts in each cohort and zero for control analysts in the cohort. *Post* is an indicator variable that equals one for both treated and control analysts in the cohort starting in the first quarter when the treated analyst's city implements the monitoring program and remains one for all subsequent quarters. All variables are defined in the Variable Appendix in the paper. Standard errors are clustered at the City × Year level and reported in parentheses. *, **, *** indicate statistical significance at the 10%, 5%, and 1% levels (two-sided), respectively.

Internet Appendix C Large Language Model

C.1 Model performance

C.1.1. Air Pollution Discussed

In this section, we evaluate the performance of the large language model *DeepSeek-R1*, which we use to identify whether an analyst report discusses air quality—our *Air Quality Discussed* variable. We randomly selected 500 analyst reports and hired two research assistants (RAs) to manually and independently classify whether each report discusses air quality, following the SASB definition. For the small number of reports where the two RAs disagreed (fewer than 1%), one of the coauthors reviewed the report and made the final determination. We then assessed the model's performance against this benchmark. Table C1, Panel A, reports the confusion matrix for the model. Out of 500 reports, the model correctly classifies 495: 35 reports identified as discussing air quality (true positives) and 460 identified as not discussing air quality (true negatives). The model misclassifies 2 reports as discussing air quality when they do not (false positives) and 3 reports as not discussing air quality when they actually do (false negatives).

Column 1 of Panel D reports several standard classification metrics to evaluate the model's performance. The results indicate that *DeepSeek-R1* is highly reliable, accurately classifying 99% of the reports. These findings demonstrate the model's effectiveness in identifying discussions of air quality in analyst reports. The precision—defined as the proportion of true positives among all reports the model classified as discussing air quality—is 94.6%. The recall—defined as the proportion of actual air quality-related reports correctly identified by the model—is 92.1%. The resulting F1-score, the harmonic mean of precision and recall, is 93.3%. These metrics suggest that *DeepSeek-R1* performs well in identifying relevant reports while maintaining a low rate of both false positives and false negatives. These performance metrics are comparable to those reported in prior studies that apply large language models in various contexts (e.g., Li et al., 2025).

C.1.2. Brown, Neutral, Green

In this section, we evaluate the performance of *DeepSeek-Reasoner* for classifying firms into brown, neutral, or green. We randomly selected 100 annual reports issued by firms covered by analyst reports in our sample. Two research assistants (RAs) manually and independently classify a firm as Brown (Green) if its business description indicates that the firm faces risks or costs (gains an advantage or opportunity) from heightened attention to, concern about, and regulation of air quality issues, as defined by the SASB. Firms not classified as Brown or Green are designated Neutral. We then assessed the model's performance against this benchmark.

Table C1, Panel B, reports the confusion matrix for the model focusing on brown firms. Out of 100 firms, the model correctly classifies 98: 14 firms identified as brown (true positives) and 84 firms identified as non-brown (true negatives). The model misclassifies 1 firm as brown when it is neutral (false positive) and 1 firm as neutral when it is brown (false negative). Table C1, Panel C, reports the confusion matrix focusing on green firms. Column 2 of Panel D reports several standard classification metrics to evaluate the model's performance, focusing on brown firms. The results indicate that *DeepSeek-Reasoner* is highly reliable, accurately classifying 99% of the firms. The precision, recall, and F1-score are 93%. Column 3 of Panel D reports similar performance for green firms.

C.2 Choice of language model

We choose *DeepSeek-R1* over other large language models (e.g., *GPT-4o*) for three reasons.

Data confidentiality: Our analyst reports are proprietary. *DeepSeek* can be deployed and run locally on our own machines, ensuring that all data remains on our internal systems. In contrast, most proprietary models (e.g., *GPT-4*, *Claude*) are only accessible via paid APIs, which require transmitting data to external servers—raising

confidentiality and compliance concerns.

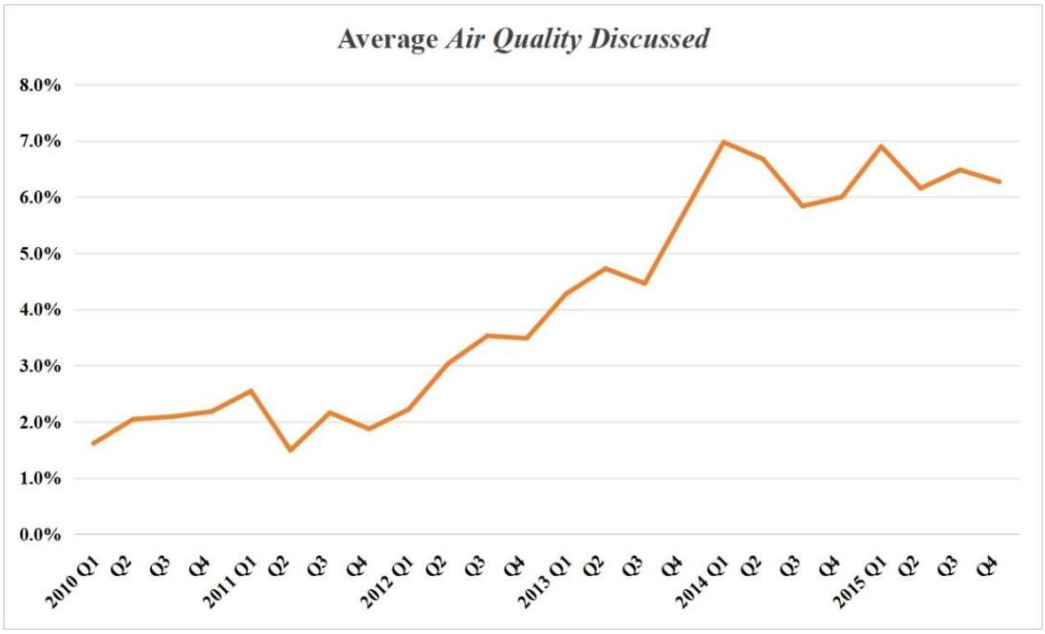
Comparable performance to proprietary models: In our setting, *DeepSeek* performs as well as *GPT-4o*. When evaluated using the same prompt, *GPT-4o* yields the exact same performance metrics as *DeepSeek* in our setting. Although the two models misclassify different individual reports, the number and type of errors are identical. This indicates that *DeepSeek* matches *GPT-4o*'s effectiveness in classifying analyst reports, despite being open-source, locally deployable, and free of per-token costs.

Cost: The cost of using *DeepSeek* is limited to computational infrastructure, as the model is open-source and can be run locally. In contrast, proprietary models are typically accessed via paid APIs, where charges accumulate based on the number of tokens processed. Our estimates suggest that these per-token costs can be substantial—particularly in our setting, where we generate multiple outputs from each report, including measures for whether air quality and social capital are discussed.

References

Li, K., Mai, F., Shen, R., Yang, C., and Zhang, T. (2025). Dissecting corporate culture using generative ai. Technical report, Working paper, https://papers. ssrn. com/sol3/papers. cfm.

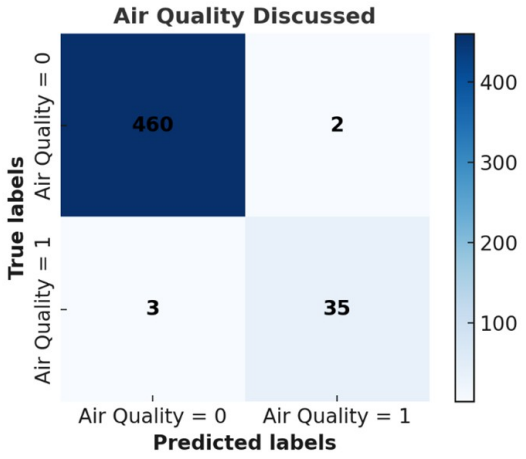
Figure C1. Time trend in *Air Quality Discussed* measure



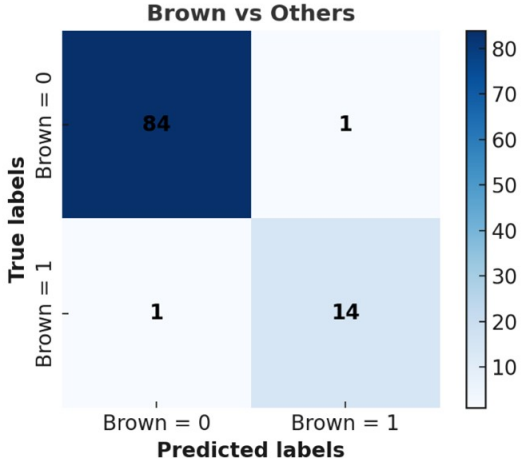
Notes: This figure presents the trend in the average of our *Air Quality Discussed* measure. *Air Quality Discussed* is an indicator variable that equals one if the analyst's report discusses air quality as defined by the SASB and measured using a large language model (*DeepSeek-R1*).

Table C1. *DeepSeek* classification performance

Panel A. *Air Pollution Discussed*



Panel B. *Brown* vs Others



Panel C. *Green* vs Others

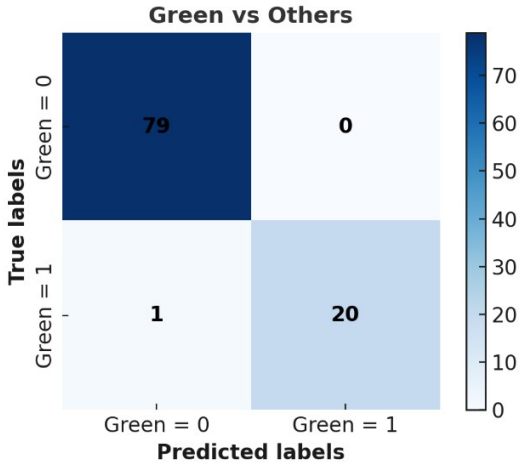


Table C1 (Continued)

Panel D. Model performance metrics

Metric	*Air Pollution Discussed*	Brown vs Others	Green vs Others
Accuracy	99.0%	98.0%	99.0%
Precision	94.6%	93.3%	100.0%
Recall	92.1%	93.3%	95.2%
F1 Score	93.3%	93.3%	97.6%

Notes: This table presents the performance of the large language model *DeepSeek-R1*, which we use to identify whether an analyst report discusses air quality—our *Air Quality Discussed* variable. We randomly selected 500 analyst reports and hired two research assistants (RAs) to manually and independently classify whether each report discusses air quality, following the SASB definition. We then assessed the model's performance against this benchmark. Similarly, we randomly selected 100 annual reports issued by firms covered by analyst reports in our sample. Two research assistants manually and independently classify a firm as Brown (Green) if its business description indicates that the firm faces risks or costs (gains an advantage or opportunity) from heightened attention to, concern about, and regulation of air quality issues, as defined by the SASB. Firms not classified as Brown or Green are designated Neutral. We then assessed the model's performance against this benchmark.

Panels A-C report the confusion matrix for the model. Panel D presents the performance metrics for the model.

$$\text{Accuracy} = \frac{\text{TP} + \text{TN}}{\text{TP} + \text{TN} + \text{FP} + \text{FN}}$$

$$\text{Precision} = \frac{\text{TP}}{\text{TP} + \text{FP}}$$

$$\text{Recall} = \frac{\text{TP}}{\text{TP} + \text{FN}}$$

$$\text{F1 Score} = 2 \times \frac{\text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}}$$

where,

For *Air Quality Discussed*:
TP (True Positives) occur when the model predicts that a report discusses air quality and the report actually does. TN (True Negatives) occur when the model predicts that a report does not discuss air quality and this is correct. FP (False Positives) refer to cases where the model incorrectly predicts that a report discusses air quality when it does not. FN (False Negatives) occur when the model fails to identify a report that does discuss air quality, instead predicting that it does not.

For *Brown group*: TP (True Positives) occur when the model predicts that a firm belongs to the Brown group and it actually does. TN (True Negatives) occur when the model predicts that a firm does not belong to the Brown group and this is correct. FP (False Positives) refer to cases where the model incorrectly predicts that a firm belongs to the Brown group when it does not. FN (False Negatives) occur when the model fails to identify a firm that belongs to the Brown group, instead predicting that it does not.

For *Green group*: TP (True Positives) occur when the model predicts that a firm belongs to the Green group and it actually does. TN (True Negatives) occur when the model predicts that a firm does not belong to the Green group and this is correct. FP (False Positives) refer to cases where the model incorrectly predicts that a firm belongs to the Green group when it does not. FN (False Negatives) occur when the model fails to identify a firm that belongs to the Green group, instead predicting that it does not.

Internet Appendix D Examples of air pollution discussions in analyst reports

Example D1. Regulatory Risks and Preference-related Factors
Environmental regulations increase demand for the firm's low-emission solutions

- **Report date**: 17-May-2013
- **Firm**: Weichai Heavy Machinery Co., Ltd
- **Business Description**: The company develops, manufactures, and sells powertrain systems and engine products (e.g., for marine propulsion and commercial vehicle applications), including engines compatible with LNG.
- **Industry**: Manufacturing - General equipment manufacturing
- **Analyst**: Shuwei Wang (Broker: Essence Securities)
- **City**: Shanghai

Chinese texts: 液化天然气具有明显的节能减排效应，由于价格相对较低，经济成本优势明显，未来随着降低排放相关政策的落实执行，使用 LNG 加柴油混合动力的船舶将成为今后绿色航运的主要贡献因素之一。LNG发动机排放的氮氧化物只有柴油发动机排放的25%，碳氢化合物和碳氧化合物分别只有30%和12%，颗粒物的排放几乎为零。中长期角度看，主要受益于国家"气化内河、绿色航运"战略开启，我们测算，潍柴重工的内河船舶LNG发动机每年的市场规模49.5亿元。

English Translation: Liquefied natural gas (LNG) has significant energy-saving and emission-reducing effects. Due to its relatively low price, it offers significant economic cost advantages. Looking ahead, as policies aimed at reducing emissions are implemented and enforced, ships using LNG-diesel hybrid power will become one of the main contributing factors to green shipping. LNG engines emit only 25% of the nitrogen oxides emitted by diesel engines, 30% of hydrocarbons, 12% of carbon monoxide, and almost zero particulate matter. In the medium to long term, driven mainly by the launch of the national strategy of *'gasify inland waterways and promote green shipping,'* we estimate that the *annual market size* of Weichai Heavy Machinery's inland-waterway LNG marine engines will increase to 4.95 billion yuan.

Example D2. Regulatory Risks and Preference-related Factors
Environmental regulations reduce demand for the firm's electricity generated from traditional, coal-based power plants

- **Report date**: 7-Jun-2012
- **Firm**: Chongqing Jiulong Electric Power Co., Ltd
- **Business Description**: The company produces and sells electric power primarily through coal-fired thermal power generation.
- **Industry**: Production and supply of electricity, heat, gas and water
- **Analyst**: Dajun Li (Broker: Huachuang Securities)
- **City**: Beijing (Monitoring program implementation date: 21-Jan-2012)

Chinese texts: 受环保政策不断加强及PM2.5治理深化的影响，煤炭消费与发电排放面临进一步限制，公司传统发电资产需求放缓、盈利承压。为顺应政策导向并优化资产结构，公司主动剥离全部非环保资产，将资源聚焦于脱硫、脱硝、除尘等持续增长的环保业务，实现向专业化环保平台的战略转型。

English Translation: As *environmental policies continue to tighten* and PM2.5 control efforts deepen, coal consumption and emissions from power generation face further restrictions. *Demand for the company's traditional power-generation assets has slowed*, putting pressure on profitability. To align with policy directions and optimize its asset structure, the company has proactively divested all non-environmental assets and reallocated resources toward fast-growing environmental protection businesses such as desulfurization, denitrification, and dust removal, achieving a strategic transformation into a specialized environmental protection platform.

Example D3. Regulatory Risks
Stricter environmental standards require higher environmental-protection investment by the firm

- **Report date**: 11-Apr-2013
- **Firm**: Dongjiang Environmental Company Limited
- **Business description**: The company is engaged in the treatment, recycling, and disposal of industrial and municipal waste (, including hazardous waste management and valuable materials recovery).
- **Industry**: Manufacturing industry - Comprehensive utilization of waste resources
- **Analyst**: Yu Wu (Broker: Sinolink Securities)
- **City**: Shanghai (Monitoring program implementation date: 27-Jun-2012)

Chinese texts: 环境保护部近期颁布了新版污染物排放标准，对多项排放限值作出显著收紧，其中铜、铅等重金属的排放控制要求提升尤为明显。根据新规，相关企业须大幅削减污染物排放量，减排幅度显著超越既往标准。为满足合规要求，企业预计需要对现有环保设施进行升级改造，增加处理环节，或引入更为先进的污染控制技术。初步评估显示，相关环保投入较当前水平将上升约30%至50%。

English Translation: The Ministry of Environmental Protection recently introduced a revised set of *pollutant-emission standards* that significantly tighten multiple emission limits, with especially notable increases in control requirements for heavy metals such as copper and lead. Under the updated rules, affected firms must substantially reduce pollutant emissions, with required reductions materially exceeding prior standards. To meet compliance requirements, the company is expected to upgrade and retrofit existing environmental-protection facilities, add additional treatment stages, or adopt more advanced pollution-control technologies. A preliminary assessment suggests that related environmental capital expenditures are likely to increase by approximately 30% to 50% compared to the current levels.

Example D4. Preference-related Factors
Changes in end-consumer preferences and environmental awareness motivate the firm to expand production capacity for environmentally friendly products, which is expected to improve performance

- **Report date**: 21-Apr-2013
- **Firm**: Wanhua Chemical Group Co.,Ltd.
- **Business description**: The company develops, produces, and sells chemical products.
- **Industry**: Manufacturing industry - Chemical raw materials and chemical products manufacturing industry
- **Analyst**: Ling Cao (Broker: Hua Chuang Securities)
- **City**: Beijing (Monitoring program implementation date: 21-Jan-2012)

Chinese texts: 公司战略性地将涂料产业链作为重点发展方向，计划在宁波、珠海及烟台分别布局10万吨、20万吨及40万吨水性涂料产能，合计规划产能达70万吨。这一布局的推进，是顺应终端消费市场结构性变化的结果：随着公众环保意识提升与健康居住需求日益增强，市场对低挥发性、环境友好型涂料的需求显著增长。因此，公司明确聚焦于环保型水性涂料领域，主要涵盖丙烯酸系列与聚氨酯水性涂料产业链中的涂料树脂、助剂等高附加值环节。涂料树脂与助剂作为水性涂料产业链中技术壁垒最高、盈利性较强的关键部分，将持续受益于这一由消费升级驱动的市场趋势，成为公司未来高性能、高附加值产品线的重要组成部分。

English Translation: The company has strategically identified the coatings industry as a key area for development and plans to establish water-based coatings production capacity of 100,000 tons, 200,000 tons, and 400,000 tons in Ningbo, Zhuhai, and Yantai, respectively, for a total planned capacity of 700,000 tons. *This expansion reflects structural changes in end-consumer demand: as public environmental awareness increases and demand for healthier living environments rises, market demand for low-VOC, environmentally friendly coatings has grown significantly.* Accordingly, the company is focusing on environmentally friendly water-based coatings ... Coating resins and additives are expected to continue benefiting from this consumption-upgrade-driven market trend and to become an important part of the company's future portfolio of high-performance, high value-added products.

Example D5. Physical Risks
Severe weather disrupted a shipping firm's operations

- **Report date: 25-Mar-2014**
- **Firm**: China Merchants Energy Shipping Co., Ltd.
- **Business description**: The company specializes in long-distance maritime transportation.
- **Industry**: Transportation, warehousing and postal services - Water transport industry
- **Analyst**: Tao Chang (Broker: China Merchants Securities)
- **City**: Beijing (Monitoring program implementation date: 21-Jan-2012)

Chinese texts: 2013年，油轮需求旺季的北半球冬季雾霾、大风等恶劣天气频发，影响港口作业，压港天数增加，进一步消减了有效运力的供应。在此背景下，以招商轮船为代表的专业航运运营商面临更为明显的运营压力。

English Translation: In 2013, during the peak tanker demand season, the Northern Hemisphere experienced frequent episodes of severe weather, such as haze and strong winds, which *disrupted port operations*. This led to longer port congestion and increased waiting days, further reducing the supply of effective shipping capacity. Against this backdrop, specialized shipping operators, represented by China Merchants Energy Shipping, faced even more pronounced operational pressures.

Example D6. Other Risks
The Firm's air-pollution-control capabilities facilitate financing via green bonds

- **Report date**: 21-May-2013
- **Firm**: Fujian Longking Co., Ltd.
- **Business description**: The company develops, manufactures, installs, and operates air-pollution control equipment
- **Industry**: Special equipment manufacturing industry
- **Analyst**: Wei Wang (Guotai Junan Securities)
- **City**: Shanghai (Monitoring program implementation date: 27-Jun-2012)

Chinese texts: 在国家绿色金融政策持续深化的背景下，龙净环保依托其在空气污染治理领域的业务积累，精准契合了绿色债券市场的融资导向。该公司于2012年发行的8亿元中期票据，充分体现了其绿色产业属性在资本市场的认可度，并为公司后续发展提供了关键的资金保障。

English Translation: Against the backdrop of China's continued deepening of green finance policies, Longking Environmental Protection has leveraged its established capabilities in air-pollution control to align closely with the financing priorities of the *green bond* market. The company's issuance of RMB 800 million medium-term notes in 2012 reflected the capital market's recognition of its green-industry positioning and provided critical financial support for its subsequent development.