Pollution Monitoring and the Pricing of Environmental Risk in Firms*

Namrata Kala†, Jalal Sani‡, Nemit Shroff§, and Pengdong Zhang¶

October 20, 2026

Abstract

We study whether environmental information affects asset prices by changing what sophisticated intermediaries attend to. Exploiting the staggered rollout of China's air quality monitoring program, we compare analysts covering the same firm but located in cities with different monitoring status. Monitoring increases analysts' discussion of pollution and shifts market reactions: reports by treated analysts generate more negative returns for brown firms and more positive returns for green firms. These effects do not subsequently reverse. Treated analysts also increase site visits and forecast accuracy. Environmental monitoring therefore facilitates the incorporation of environmental risk into prices through greater attention and information production.

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

*We received helpful comments from Jed Neilson, Paul Richardson (discussant), Naomi Soderstrom (discussant), Alison Taylor (discussant), Scott Wang (discussant), and workshop participants at Boston College, Dishui Lake Advanced Finance Institute, MIT, NYU Shanghai, Penn State University, University of Michigan, University of North Carolina at Chapel Hill, and University of Saskatchewan, as well as conference participants at the 7th Analyst Research Conference, the 2026 Climate Finance & Sustainability Conference, the 2026 Emerging Scholar Sustainability Research Camp, and the 2026 Lisbon Accounting Conference. We thank Yalin Luo and Yidan Mao for stellar research assistance.

†MIT Sloan, NBER, and CEPR, kala@mit.edu

‡UIUC Gies, jsani@illinois.edu

§MIT Sloan, shroff@mit.edu

¶Sun Yat-sen University, zhangpd3@mail.sysu.edu.cn

1. Introduction

Environmental externalities such as pollution and climate change impose substantial economic costs on the global economy (Dell et al., 2012; Kuehn, 2014). Two important forces can induce emitting firms to internalize these costs. Environmental regulation (e.g., Pigouvian taxes, emission limits) raises the private cost of pollution, while shifts in consumer demand can reduce revenues for high carbon footprint firms and increase revenue for cleaner alternatives as consumers become more concerned about environmental harms. However, for these forces to affect capital allocation, financial markets must incorporate their implications for firms' expected cash flows and valuations. If market participants underweight or otherwise fail to fully process information about environmental risks, stock prices may not reflect the costs and opportunities created by environmental regulation and changing consumer preferences. This raises a fundamental question: what causes sophisticated market participants to pay greater attention to environmental risk and incorporate it into firm valuations?

In this paper, we study whether making local environmental risk more salient changes how sophisticated market participants incorporate such risk into firm valuations. We focus on financial analysts, whose assessments of firms' future cash flows and investment prospects can influence stock prices.[1] Specifically, we ask whether heightened pollution salience changes analysts' assessments of the regulatory and demand-related environmental risks facing the firms they cover and, in turn, their expectations of firms' future earnings and value.

We study this question using the large-scale expansion of China's ambient air pollution monitoring network. Beginning in 2012, China launched a nationwide network of monitoring stations that reported real-time concentrations of six major air pollutants, together with a composite Air Quality Index (AQI).[2] Importantly, the monitoring network was introduced at different times across cities, generating plausibly exogenous variation in the salience of pollution for analysts based on their city of residence. We exploit this staggered rollout using a difference-in-differences (DiD) and event-study design that compares changes in an analyst's outputs (e.g., earnings forecasts, stock recommendations) before vs. after monitoring is introduced in the analyst's city with contemporaneous changes in the outputs of other analysts covering the same firm in the same period but residing in cities where monitoring has not yet been introduced. This within-firm-time comparison holds constant the firm-specific fundamentals and information common to

[1] Analysts have strong incentives to issue accurate forecasts and profitable stock recommendations, because superior performance reduces turnover risk and improves career outcomes, such as promotion to a high-status brokerage house (e.g., Mikhail et al., 1999; Hong and Kubik, 2003).

[2] The six common pollutants are fine 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).

analysts covering the firm, while the event-study design allows us to assess whether the outputs of treated and control analysts exhibit similar trends prior to the rollout.

We hypothesize that when pollution becomes more salient, financial analysts devote greater attention to environmental risks when evaluating the firms they cover, regardless of firm location. This heightened attention can affect analysts' judgments through two related channels. First, analysts may assign greater weight to publicly known information about firms' exposure to environmental risks, including current and anticipated changes in environmental regulation and consumer preferences. Second, greater attention to these risks may increase analysts' incentives to acquire additional firm-specific information needed to assess their implications for future cash flows. Our prediction builds on 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 et al., 2022). In these models, changes in the environment can alter which attributes or risks command attention, causing decision makers to place greater weight on salient considerations relative to others that are equally available but less prominent. Applied to our setting, the monitoring program can affect analysts' assessments not because treated analysts receive pollution information unavailable to others—the monitoring data are publicly available—but because pollution becomes more salient to analysts residing in treated cities. This heightened salience may lead treated analysts to place greater weight on existing information about environmental risks and to acquire additional firm-specific information about how those risks affect the firms they cover.

Because the monitoring program was rolled out at different times across cities, we follow de Chaisemartin and D'Haultfoeuille (2020) and Baker et al. (2022) and construct treatment cohorts based on the quarter in which the program is introduced in a city. We employ a stacked cohort DiD design that includes Firm $\times$ Year-Quarter $\times$ Cohort and Analyst $\times$ Firm $\times$ Cohort fixed effects. The former set of fixed effects absorbs all firm-specific factors that are common to analysts covering the same firm in the same quarter, including the firm's financial performance, environmental exposure, and disclosures, as well as pollution information from the firm's location. Identification therefore comes from comparing treated and not-yet-treated analysts covering the same firm at the same time. The latter set of fixed effects further absorbs persistent differences across analyst-firm pairs, such as analyst ability, analyst-manager ties, and geographic proximity. Thus, our estimates capture differential changes in analysts' outputs following the introduction of monitoring in their own city, relative to analysts covering the same firm whose cities have not yet adopted the program.

We first examine whether the monitoring program changes analysts' attention to environmental issues. When monitoring is introduced in a city, analysts based there

become more than twice as likely to discuss air pollution in their reports relative to not-yet-treated analysts covering the same firm in the same period. In contrast, we find no corresponding increase in discussions of other non-financial topics, such as human capital or social issues. This pattern suggests that the treatment does not induce a general increase in attention to non-financial considerations. Rather, it specifically increases analysts' attention to environmental risks, consistent with the monitoring program heightening the salience of pollution.

We next examine which types of environmental risk receive greater attention when pollution becomes more salient. We classify analysts' pollution-related discussions into categories, including regulatory risks, changes in consumer preferences and demand, and physical risks. We find that analysts primarily increase their discussion of regulatory risks and potential shifts in consumer demand, including the implications of these changes for firm sales. Moreover, the increase spans both risks that are already affecting firms and those that analysts anticipate may arise in the future. By contrast, analysts rarely discuss physical or other environmental risks. Taken together, these findings suggest that heightened pollution salience directs analysts' attention toward channels through which environmental concerns can affect firms' current and expected future cash flows.

If heightened pollution salience leads analysts to pay greater attention to financially material environmental risks, its effects should vary with firms' exposure to those risks. In particular, greater attention to environmental risk should lead to more favorable assessments of firms that stand to benefit from stricter environmental regulation or shifts in consumer demand, and less favorable assessments of firms that are likely to bear greater costs. To examine this prediction, we use an LLM-based classification that categorizes firms as green (e.g., low emission firms or producers of environmentally friendly goods such as electric vehicles), brown (e.g., high emission firms such as coal-fired power plants), or environmentally neutral. We find that the increase in pollution-related discussion in treated analysts' reports is significantly larger for both green and brown firms than for neutral firms, relative to the corresponding change among control analysts' reports covering the same firms.

We next examine whether these changes in analysts' assessments are reflected in stock prices. We find that the market reaction to treated analysts' reports becomes systematically related to firms' environmental exposure following the introduction of monitoring. Specifically, the three-day cumulative abnormal return around a treated analyst's report is more negative for brown firms and more positive for green firms, relative to reports issued by control analysts covering the same firms in the same periods. These findings suggest that treated analysts' reports convey value-relevant information about firms' exposure to environmental risk.

We next examine whether these price responses reflect improved incorporation of environmental risk or temporary overreaction. We find no evidence that the initial price reactions reverse over either the subsequent month or year, which is inconsistent with a transitory salience-induced mispricing explanation. Moreover, when a larger share of the analysts covering a green or brown firm has been treated, subsequent earnings announcements generate significantly smaller stock-price reactions. This finding suggests that information relevant to firm value is incorporated into prices earlier, consistent with treated analysts' reports helping investors update their assessments of firm value before earnings are announced. Taken together, the market reactions to analyst reports, the absence of subsequent return reversals, and the reduced information content of future earnings announcements indicate that heightened pollution salience leads environmental risk to be incorporated into stock prices more quickly.

The economic magnitudes are substantial. A back of the envelope calculation implies cumulative market-value gains of approximately $35 billion across treated analysts' reports on green firms and cumulative market-value losses of approximately $139 billion across their reports on brown firms following the program's implementation. The sum of the absolute values of these effects is approximately 5% of the total capitalization of China's stock market in the year before monitoring was introduced. These estimates suggest that ambient pollution monitoring can have economically meaningful capital-market consequences by increasing the salience of both current and anticipated environmental risks.

We next examine how heightened pollution salience affects analysts' valuation assessments and information-acquisition efforts. We first consider analysts' quantitative outputs. For brown firms, treated analysts issue more pessimistic earnings forecasts, lower target prices, weaker stock recommendations, and reports with more negative tone relative to control analysts covering the same firms in the same periods. The opposite pattern holds for green firms, while we find little change for environmentally neutral firms. These directional revisions closely mirror the stock-price responses documented above: treated analysts become more pessimistic about brown firms and more optimistic about green firms, and investors respond accordingly.

Second, we examine whether heightened pollution salience also induces analysts to acquire additional firm-specific information. Corporate site visits provide an important setting for this test because they allow analysts to gather soft information, interact directly with management, and better understand firm-specific risks that may be difficult to assess from public disclosures alone (Cheng et al., 2016; Chen et al., 2022). If greater pollution salience motivates analysts to investigate how environmental risks affect the firms they cover, we expect treated analysts to increase their site visits particularly for green and

brown firms, for which such risks are most financially material. Consistent with this prediction, treated analysts become approximately four times as likely to visit green firms and 2.5 times as likely to visit brown firms, relative to control analysts, while we find no corresponding increase for environmentally neutral firms. Moreover, when a larger share of the analysts attending a site visit has been treated, air pollution is significantly more likely to be discussed during the visit, again only for green and brown firms.

We also test and find that treated analysts issue more accurate earnings forecasts following the introduction of monitoring, with the improvement concentrated among green and brown firms. This pattern is more consistent with heightened pollution salience directing analysts' attention toward financially material environmental risks than with a behavioral bias that causes them to place excessive weight on pollution at the expense of other value-relevant information.

Finally, we conduct a broad set of robustness tests. First, our results are insensitive to alternative specifications, including a conventional staggered DiD design with two-way fixed effects, the inclusion of time-varying analyst–firm controls, the sequential exclusion of individual treatment cohorts, and alternative approaches to clustering standard errors. Second, our inferences are robust to sample restrictions designed to further isolate analysts' local exposure to pollution monitoring. In particular, the increase in pollution-related discussion remains when we exclude reports on firms located in cities that have adopted the monitoring program and when we exclude analysts covering firms headquartered in their own city. Third, we implement an alternative research design using Chinese firms cross-listed in the U.S. or Hong Kong, which are covered by both mainland Chinese and foreign analysts. This design compares changes in the reports of mainland analysts, who are locally exposed to the rollout of pollution monitoring, with those of foreign analysts covering the same firms. The results from this alternative design are consistent with our main findings.

The paper relates to three literatures. Most broadly, we contribute to the literature on the pricing of environmental risk in financial markets.[3] One strand of this literature examines how salient environmental experiences, such as hurricanes, floods, heat waves, or local pollution, affect the beliefs and behavior of market participants and managers (e.g., Dessaint and Matray, 2017; Alok et al., 2020; Choi et al., 2020; Bourveau and Law, 2021; Correa et al., 2026). A second strand studies how firm-specific environmental disclosures and news affect firms, investors, and asset prices (e.g., Chen et al., 2018; Bolton and Kacperczyk, 2021, 2023; Downar et al., 2021; Pastor et al., 2022; Ilhan et al., 2023; Tomar, 2023; Derrien et al., 2025;

[3]This work is also related to research showing that macroeconomic conditions shape financial market participants' beliefs and behavior more broadly (Malmendier et al., 2020).

Zhang, 2025). Our setting allows us to isolate a distinct channel through which environmental risk becomes incorporated into asset prices. Unlike settings in which salience arises from environmental shocks such as hurricanes or heat waves, the increase in salience we study is induced by a deliberate public-information policy. This feature suggests that policymakers can shape the salience of economically relevant risks through information provision and, in doing so, facilitate their incorporation into asset prices. In addition, unlike firm-specific disclosures, the rollout of pollution monitoring does not differentially provide treated analysts with new information about the firms they cover. Instead, it makes environmental risk more salient to some analysts than to others who cover the same firm at the same time and have access to the same publicly available pollution information. This distinction allows us to show that the pricing of environmental risk depends not only on what information is available, but also on whether sophisticated intermediaries attend to that risk and acquire the firm-specific information needed to assess its cash-flow implications. In this sense, our findings identify ambient environmental monitoring as a distinct information-policy channel through which environmental risks can become more fully reflected in asset prices.[4]

Second, we contribute to the literature on salience and attention in financial markets. Prior theoretical and empirical work shows that salient attributes, extreme returns, or attention-grabbing events can receive disproportionate weight in investor decisions and asset prices (Barber and Odean, 2008; Bordalo et al., 2012, 2013; Hartzmark, 2015; Hartzmark and Shue, 2018; Frydman and Wang, 2020; Cosemans and Frehen, 2021; Barber et al., 2022; Cakici and Zaremba, 2022). Our evidence highlights a different role for salience. When the underlying risk is financially material and agents have strong incentives to form accurate assessments, greater salience can improve rather than distort decision-making. In our setting, treated analysts devote greater attention to environmental risks, acquire additional firm-specific information, and produce more accurate forecasts, while the associated stock-price responses do not subsequently reverse. Thus, salience can enhance information production and price discovery rather than merely induce excessive weighting of salient information.

Finally, we contribute to research on the consequences of China's air pollution monitoring program. Prior studies show that the program increased awareness of pollution and induced households to undertake defensive actions, including purchasing health insurance, masks, and

[4]In related work, Fisman et al. (2026) find that retail investors reduce their holdings of brown stocks following the rollout of pollution monitoring. Our analysis complements theirs by focusing on financially sophisticated intermediaries and the process through which environmental risk enters prices. We show that monitoring changes analysts' assessments of specific cash-flow channels, including current and anticipated regulatory and demand-related risks; induces greater firm-specific information acquisition; improves forecast accuracy; and generates stock-price effects that persist and are associated with greater price efficiency.

air purifiers (Chang et al., 2018; Xie et al., 2023; Barwick et al., 2024). We show that the program also has important financial-market consequences. As such, our findings identify a previously unexplored capital-market channel through which environmental monitoring can affect economic outcomes.

2. Context

2.1. Background on Pollution Monitoring

China has made remarkable strides to balance environmental quality and economic growth in recent decades (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 this information. Prior work finds that there was widespread manipulation of pollution data prior to 2012 (e.g., Greenstone et al., 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. In addition, discrepancies between different monitoring sites that are geographically proximate would trigger alerts.

Second, the MEP established a real-time information dissemination system, which directly controls pollution monitors and automatically transmits the pollution data collected to its 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. Prior research finds that the program eliminated opportunities for local governments to misreport air pollution data (Greenstone et al., 2022).

Under the monitoring program rollout, cities were 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

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

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 are 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.

2.2. Descriptive Evidence of Ambient Monitoring's Impact on Pollution Awareness and Salience

We provide evidence suggesting that China's real-time pollution monitoring program led to a sharp and abrupt increase in public access to local air quality information, substantially increasing public awareness of air pollution. Our evidence is consistent with Barwick et al. (2024), who find that the program's implementation led to nationwide awareness about air quality, with a key difference that the analysis in this section is restricted to cities where stock analysts are located. This increase in salience about pollution acts as a first stage for the main analysis on the impacts on financial markets.

To document changes in individuals' information consumption following the program's rollout, we examine its effect on two 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 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 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 "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.

3. Empirical Strategy

3.1. Specification to Estimate Change in Salience of Pollution

To estimate the impact of the program's implementation on the frequency of media coverage of air pollution, we employ a stacked-cohort DiD design following de Chaisemartin

[6]Specifically, if the rollout occurs in the first half of a quarter, we define the rollout quarter as that quarter; if it occurs in the second half of the quarter, we define the rollout quarter as the subsequent quarter.

and D'Haultfoeuille (2020) and Baker et al. (2022). The program was adopted by the 17 cities in our sample in six distinct quarters between 2012Q1 and 2013Q4. For each adoption quarter, we construct a separate cohort in which cities adopting in that quarter constitute the treated group and cities adopting in later quarters serve as not-yet-treated controls. For example, in the first cohort, cities adopting in 2012Q1 are treated, while cities adopting after 2012Q1 serve as controls until their own adoption. Because cities in the final adoption quarter have no later-treated cities available to serve as controls, we do not use them as treated observations. We therefore construct five treatment cohorts and stack them into a single sample to estimate the following specification:

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

where *city*, q, and c index cities, calendar year-quarters, and treatment cohorts, respectively. y is either *News Coverage*, defined as the number of newspaper articles in a city-quarter that contain air pollution–related keywords in the title and reference the city in the article text, or *Internet Search*, the average daily frequency of Baidu searches for those keywords in a city-quarter. Because these two variables are non-negative count variables, we estimate Equation 1 using a Poisson specification, following Cohn et al. (2022) and Chen and Roth (2024). $Treated\ City_{city,c}$ equals one for cities treated in cohort c and zero for the not-yet-treated control cities in that cohort. $Post_{q,c}$ equals one for all observations in cohort c beginning in the quarter in which the treated cities adopt the monitoring program and remains one thereafter. $\alpha_{city,c}$ and $\alpha_{q,c}$ denote City $\times$ Cohort and Year-Quarter $\times$ Cohort fixed effects, respectively. The former absorb time-invariant differences across cities within a cohort, while the latter absorb shocks common to all cities in a given quarter within that cohort. We cluster standard errors at the City-Year level.[7]

3.2. Main Specification

Our main specification follows the same stacked-cohort DiD logic as the city-level analysis above, but shifts the unit of analysis from the city-quarter to the analyst-report level, allowing us to compare analysts covering the same firm at the same time. The program increased the availability and timeliness of publicly reported air quality data, but these data were accessible to analysts regardless of where they resided. Thus, the rollout did not differentially change treated and control analysts' access to pollution information. Instead, because monitoring became operational at different times across cities, it generated variation in analysts' local exposure to—and hence the salience of—pollution information. Accordingly, among analysts

[7]We cluster at the City-Year level rather than the City level because our sample contains only 17 cities, which may be too few clusters for reliable inference (Petersen, 2009). Our inferences are robust to clustering standard errors at the City level.

covering the same firm in the same period, those residing in cities where monitoring had been introduced experienced a greater increase in the salience of pollution than analysts residing in not-yet-treated cities.

Our primary identifying assumption is that, conditional on the fixed effects described below, the introduction of pollution monitoring does not differentially change the firm-specific information available to treated and control analysts covering the same firm. Analysts may differ in their overall information levels; our design requires only that the change in firm-specific information around the rollout is similar across treated and control analysts. Under this assumption, differential changes in analysts' outputs—such as report content, earnings forecasts, or stock recommendations—can be attributed to variation in the local salience of pollution rather than to differential changes in information about the firm.[8] Panel (a) of Figure A1 in the Internet Appendix shows the distribution of analyst reports across treatment cohorts and calendar time. Panels (b) and (c) illustrate the stacked-cohort construction for the first two cohorts.

We estimate the following regression using the stacked sample:

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

where i, j, q, and c index analysts, firms, calendar year-quarters, and treatment cohorts, respectively. $y_{i,j,q,c}$ denotes one of several outcomes from analyst i's report for firm j in quarter q, described in detail below. $Treated_{i,c}$ equals one for treated analysts in cohort c and zero for not-yet-treated control analysts. $Post_{q,c}$ equals one for all observations in cohort c beginning in the quarter in which monitoring is introduced in the treated analysts' cities and remains one thereafter.[9] Panels (b) and (c) of Figure A1 in the Internet Appendix illustrate the coding of *Treated* and *Post* for the first two cohorts.

The terms $\alpha_{j,q,c}$ and $\alpha_{i,j,c}$ denote Firm × Year-Quarter × Cohort and Analyst × Firm × Cohort fixed effects, respectively. The former absorb all factors common to analysts covering the same firm in the same quarter within a cohort, including the firm's emission profile, financial performance, growth prospects, shareholder base, and disclosure policies, as well as ambient environmental information disclosed in the firm's city. They also absorb any contemporaneous changes in pollution-related discussion that are common across analysts

[8] Geographic proximity can affect analysts' costs of acquiring firm-specific information (e.g., Bae et al., 2008; Chen et al., 2022). Such time-invariant differences in information associated with analyst-firm proximity are absorbed by the Analyst × Firm × Cohort fixed effects. Nevertheless, we conduct two additional tests to address this concern. First, our results are robust to excluding analysts who cover firms headquartered in the same city (Table A11 in the Internet Appendix). Second, Table A15 in the Internet Appendix shows that our results are not explained by differences in the distance between analysts and the firms they cover.

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

covering the same firm. Identification therefore comes from comparing, within the same firm-quarter-cohort, analysts residing in cities that differ in their exposure to the monitoring program.

Analyst × Firm × Cohort fixed effects absorb time-invariant characteristics of each analyst-firm pair, including persistent matching patterns, analyst-specific traits, and geographic proximity.[10] The coefficient of interest in Equation 2, β, captures the differential pre–post change in analyst outputs for treated analysts relative to not-yet-treated control analysts covering the same firm in the same period. We also estimate quarterly event-study specifications using the same fixed effects to assess pre-treatment trends.

4. Data

4.1. Data Sources and Sample Construction

We have two primary data sources. The first is the textual content of analyst research reports from the CnOpenData database, which compiles reports issued by brokerage firms across mainland China.[11] These reports contain both quantitative outputs—such as earnings forecasts, stock recommendations, and target prices—and narrative discussions of firms' performance, risks, and growth prospects. We use the report text to measure whether and how analysts discuss firms' exposure to air pollution and environmental risks, extract target-price forecasts, measure report tone, and identify the city in which the analyst is based. Our initial sample consists of 217,510 analyst reports with available textual content, issued by 3,218 unique analysts between 2010Q1 and 2015Q4 for firms listed on the Shanghai and Shenzhen Stock Exchanges.

Our second primary data source is the Chinese Research Data Services (CNRDS) platform.[12] We match each analyst report to its CNRDS record using the broker name, analyst name, covered firm's six-digit stock code, and report date. From CNRDS, we obtain analysts' EPS forecasts, stock recommendations, corporate site visits, and

[10]These fixed effects also absorb time-invariant differences in the distance between the analyst and the firm. If an analyst moves across cities during our sample period, we assign the analyst to the first city in which they are observed when the monitoring program is implemented, thereby avoiding coding the same analyst as treated more than once. Our results are robust to excluding analysts associated with more than one city during the sample period (untabulated).

[11]We purchased the CnOpenData database from a commercial data vendor, Henan Handata Information Technology Co., Ltd. Per private communication with the vendor, analyst reports are collected directly from brokerage firms in mainland China and supplemented with reports from public financial information platforms. The reports are provided as PDF files, each with a unique report ID, together with a companion dataset linking each report ID to the covered firm's stock code, analyst name, brokerage name, and analyst report date.

[12]Specifically, we use the Chinese Broker and Financial Analysts System (CBAS) database accessed through CNRDS. CNRDS is owned and operated by Shanghai Jing He Information Technology Co., Ltd. Prior studies often rely on the CSMAR database for financial analyst forecasts and characteristics. We use CNRDS because it provides more comprehensive coverage of financial analysts in China: over the 2010–2015 period, CNRDS contains 303,734 analyst reports, compared with 218,369 in CSMAR.

characteristics (e.g., age), as well as firms' actual EPS. This matching step removes 203 analysts, or 6.3% of the initial sample.

We next identify analysts' locations using the area codes of phone numbers reported in their research reports and exclude reports for which no phone number is available.[13] This step removes an additional 321 analysts, or 10.6% of the remaining sample. To identify changes around the monitoring program's implementation, we further require each analyst–firm pair to have at least one report both before and after the relevant adoption date. Finally, we restrict the sample to periods before 2013Q4, the final adoption quarter, because no not-yet-treated analysts remain to serve as controls thereafter. These restrictions yield a final sample of 39,950 analyst reports issued by 715 unique analysts covering 1,460 unique firms. Table A2 in the Internet Appendix summarizes the sample-construction process, and Table 1 reports the distribution of analyst reports across cities.

We use several additional data sources. We obtain daily stock returns and stock prices from the China Stock Market & Accounting Research (CSMAR) database.[14] To classify firms as green, brown, or neutral, as described in Section 5.2.3, we use the Management's Discussion and Analysis (MD&A) sections of firms' 2011 annual reports, which we obtain from the websites of the Shanghai and Shenzhen Stock Exchanges. The MD&A is a narrative section of the annual report in which management discusses the firm's business, financial performance, strategic plans, and risks.

We also obtain news coverage of air pollution from the China National Knowledge Infrastructure (CNKI), internet search activity from the Baidu Index platform, and firm-level emissions data from the Environmental Survey and Reporting (ESR) database, which we use to construct an alternative measure of brown firms.[15] Finally, we manually collect the date on which the monitoring program was implemented in each of the 17 cities in our sample from news reports and city yearbooks, as described in Section 2.1.

4.2. Summary Statistics

Table 2 reports summary statistics for the key variables used in our analyses. On average, 2.7% of analyst reports discuss air pollution, based on our Sustainability Accounting Standards Board (SASB)-based measure (*Air Pollution Discussed*). The mean

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

[14] CSMAR is an academic research database developed by Shenzhen CSMAR Data Technology Co., Ltd. Its daily stock-price data are compiled from the official trading records of the Shanghai and Shenzhen Stock Exchanges, and returns are computed using procedures similar to those used by CRSP, including adjustments for dividends and stock splits. We use daily returns with cash dividends reinvested.

[15] CNKI's newspaper database contains full-text articles supplied by major national, provincial, and municipal newspapers in China and makes these articles available in searchable digital form. The ESR database is collected by the Ministry of Environmental Protection and contains annual establishment-level emissions and pollution information reported by major polluting establishments.

market reaction around an analyst report is 0.87%, with an interquartile range from –1.96% to 3.16%. In terms of firms' environmental exposure, 10.9% and 10.6% of the observations in our sample relate to firms classified as green and brown, respectively. As described in Section 5.2.3, we classify firms using *DeepSeek-Reasoner* applied to the MD&A sections of firms' 2011 annual reports.

4.3. Main Outcomes

We examine three sets of outcomes. The first captures analysts' attention to environmental risks. Using the textual content of analyst reports, we measure whether analysts discuss air pollution and distinguish among risk categories, including regulatory, demand-related, and physical risks. The second set captures the stock-market consequences of analysts' assessments. We examine stock-price reactions to analyst reports and the persistence of these reactions to assess whether changes in analysts' assessments are incorporated into firm valuations. The third set captures analysts' information acquisition and assessments of firm value. We examine analysts' corporate site visits and report outputs, including earnings forecasts, stock recommendations, target prices, and forecast accuracy. Together, these outcomes allow us to trace how greater attention to environmental risks affects analysts' information acquisition, their assessments of firms, and the incorporation of those assessments into stock prices.

To measure whether analysts discuss firms' air-polluting activities in their reports, we use a generative large language model (*DeepSeek-R1*) to identify whether the report explicitly discusses air quality,[16] as defined by the SASB. SASB is particularly well suited to our setting because its standards are designed from an investor perspective and identify, on an industry-by-industry basis, sustainability-related risks and opportunities that are financially material to capital providers.[17] To assess the model's performance, we manually classify 500 randomly selected reports. *DeepSeek-R1* achieves 99% accuracy, with precision of 94.6%, recall of 92.1%, and an F1 score of 93.3%.[18]

[16]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.

[17]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. 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/.

[18]Precision is the share of reports classified by the model as discussing air pollution that actually do so; recall is the share of reports that discuss air pollution that the model correctly identifies; and the F1 score is the harmonic mean of precision and recall.

We provide additional details on the large language model's performance in Internet Appendix B, and present several examples of air pollution discussions in analyst reports in Internet Appendix C. Following prior literature examining the pricing of environmental risks (e.g., Giglio et al., 2021), we further decompose air pollution discussions into physical and transition risks, and separate transition risks into their underlying components, as described in Section 5.2.2. We also verify that our inferences are robust to an alternative text-based measure based on the methodology of Lin et al. (2024), who use a word-embedding model to construct a dictionary for measuring pollution-related disclosure. Specifically, we construct an indicator, *Air Pollution Discussed–Dict*, that equals one if an analyst report contains air pollution-related words or phrases from their pollution dictionary.[19]

Second, we examine the market reaction to analyst reports to test whether changes in report content translate into changes in investor perceptions of firm value. The third set of outcomes comprises site visits (a common way for analysts to gather information about the firms they cover), forecast accuracy, and several quantitative outputs produced by analysts. These outputs include earnings per share (EPS) forecasts, stock recommendations, target prices, and report tone. We define each of these outcomes in detail when we introduce the corresponding empirical analysis.

5. Results

5.1. Changes in Salience of Pollution

Column 1 of Table 3 reports the effect of the monitoring program on media coverage of air pollution in treated cities, and Panel (a) of Figure 1 presents the corresponding event-study estimates. The coefficient on *Treated City* $\times$ *Post* is positive and significant at the 1% level, implying that media coverage of air pollution increases by approximately 160% following the introduction of monitoring in a city. The event-study estimates show no evidence of differential pre-trends in media coverage between treated and control cities, followed by a sharp increase in coverage after implementation. These findings indicate that the monitoring program substantially increases local media attention to air pollution, consistent with the program increasing the salience of air quality among residents of treated cities.

We next examine whether residents respond to the increased availability and salience of pollution information by actively seeking additional information. Column 2 of Table 3 reports results using *Internet Search* as the outcome, and Panel (b) of Figure 1 presents the

[19] 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. Because our focus is specifically on air quality, we select the subset of keywords pertaining to air quality. Specifically, we instruct *DeepSeek-R1* to assess the relevance of each keyword based on SASB's definition of air quality and 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 the code used to construct their dictionary-based measures of environmental and social disclosures.

corresponding event-study estimates.[20] The coefficient on *Treated City* × *Post* is positive and significant at the 1% level, implying an approximately 37% increase in air pollution-related search activity following program implementation. Panel (b) of Figure 1 shows similar trends in search activity in treated and control cities before implementation, followed by a sharp divergence thereafter. Together, the media coverage and internet search results provide evidence that the monitoring program increases both public attention to and information acquisition about air pollution, consistent with air pollution becoming more salient in treated cities.

5.2. Analyst Discussions of Air Pollution

Panel A of Table 4 presents the results from estimating Equation 2 with *Air Pollution Discussed* as the dependent variable, and Panel (a) of Figure 2 presents the corresponding event-study estimates. The coefficient on *Treated* × *Post* is positive and significant at the 1% level. Following the introduction of monitoring in their city, treated analysts are 2.2 percentage points more likely to discuss air pollution than not-yet-treated analysts covering the same firm in the same period. This effect represents an increase of approximately 105% relative to the pre-treatment mean of *Air Pollution Discussed*.

Panel (a) of Figure 2 plots the event-time differences in air pollution discussions between treated and control analysts over the four quarters preceding treatment and the two quarters following treatment. Specifically, we replace *Post* in Equation 2 with a series of event-time indicators, using the quarter immediately before implementation (*q-1*) as the omitted period. The estimates show no evidence of differential pre-treatment trends in *Air Pollution Discussed*, followed by a sharp and persistent increase in treated analysts' discussions of air pollution after the monitoring program is introduced in their city.

5.2.1. Placebo Test: Analyst Discussions of Other Non-financial Topics

To assess whether the monitoring program increases analysts' attention to non-financial issues more broadly, rather than specifically increasing the salience of air pollution, we conduct two placebo tests based on analysts' discussions of social topics. If the effect is specific to pollution salience, we should observe no corresponding increase in treated analysts' discussions of unrelated social issues.

We construct two outcomes based on the SASB's classification of social topics into Human Capital and Social Capital. We instruct *DeepSeek-R1* to construct indicator variables for whether an analyst report explicitly discusses human capital or social capital, as defined by SASB. Panel B of Table 4 shows no statistically significant change in treated analysts' discussions of either category. The estimated coefficients are close to zero, despite relatively

[20] The sample size in Column 2 of Table 3 is smaller than that in Column 1 because the internet search data begin in 2011, whereas the *News Coverage* sample begins in 2010.

high pre-treatment discussion rates of approximately 10% for human capital and 8% for social capital. These findings suggest that the monitoring program does not simply increase analysts' attention to non-financial issues generally, but instead specifically increases their attention to air pollution.

5.2.2. Analyst Discussions of Different Types of Environmental Risks

We next examine which types of environmental risks receive greater attention when pollution becomes more salient. We first classify environmental risks into two broad categories: physical risks and transition risks. Physical risks capture the direct physical effects of pollution or climate change on a firm's operations and assets, such as damage to facilities from extreme weather events. Transition risks capture the consequences of the economy's adjustment toward lower emissions. We further decompose transition risks into three components. First, regulatory risks capture costs imposed by, or opportunities arising from, environmental policies and regulation, such as higher costs from carbon taxes or emission limits or opportunities to help other firms comply with environmental regulations. Second, preference-related factors capture changes in consumer preferences and demand arising from pollution or climate concerns, such as reduced demand for pollution-intensive products or increased demand for products that mitigate pollution-related health risks. Third, stakeholder risks capture responses by investors, supply-chain partners, or other stakeholders to a firm's pollution- or climate-related activities, such as a higher cost of capital for high-polluting firms.[21]

We use *DeepSeek-R1* to classify the text of analyst reports into these categories. At the aggregate level, we construct indicator variables, *Physical Risks Discussed* and *Transition Risks Discussed*, that equal one if a report discusses the corresponding type of environmental risk. We similarly construct indicators for the three components of transition risk: *Regulatory Risks Discussed*, *Preference-related Factors Discussed*, and *Stakeholder Risks Discussed*. Because a report may discuss multiple channels, these categories are not mutually exclusive. Reports containing no discussion of air pollution are coded as zero for all indicators.

Examples of discussions assigned to each category are provided in Internet Appendix C. Among reports that discuss air pollution, 95% discuss transition risks. Regulatory risks and preference-related factors account for most of these discussions: 77% of pollution-related reports discuss regulatory risks and 70% discuss preference-related factors. By contrast, fewer than 10% discuss physical risks or stakeholder risks. These descriptive patterns suggest that analysts primarily view air pollution through the lens of the economy's

[21] Throughout, we use the term "risk" broadly to denote firms' exposure to pollution- and climate-related factors that may have either adverse consequences (e.g., higher costs, regulatory constraints, or reduced market share) or favorable consequences (e.g., new markets, competitive advantages, or policy support).

adjustment to environmental concerns—particularly changes in regulation and consumer demand—rather than through direct physical effects or stakeholder responses. We also assess the LLM's performance in classifying different types of environmental risk. Based on a manual classification of 100 reports that discuss air pollution, the model achieves 100% accuracy for physical risks and 98% for transition risks, with accuracy of at least 95% for each component of transition risk. The corresponding F1 scores are at least 95.9% for all risk categories except stakeholder risks, for which the F1 score is 85.7%. We provide additional details on the LLM's performance in Internet Appendix B.

Table 5 presents the results using each of these indicator variables as the dependent variable. Panel A shows that the rollout of the pollution monitoring program increases discussions of transition risks by approximately 86% relative to the pre-program mean, while the effect on physical risks is economically small and statistically insignificant. Panel B decomposes the transition-risk effect into its three components. 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 their pre-program means. By contrast, the effect on stakeholder risks is economically small and statistically insignificant.

Panel C further decomposes regulatory risks and preference-related factors into current and anticipated future components. Treated analysts significantly increase their discussion of both regulatory exposure already in place and regulation anticipated to take effect in the future. Specifically, treated analysts are 0.8 and 1.4 percentage points more likely to discuss current and future regulatory risks, respectively, with the larger point estimate corresponding to anticipated future regulation. We find a similar pattern for preference-related factors: discussions of demand shifts already affecting the firm and anticipated future demand shifts increase by 0.3 and 1.3 percentage points, respectively, again with a larger point estimate for the future component.

Taken together, these findings suggest that heightened pollution salience directs analysts' attention primarily toward transition risks, and particularly toward regulatory and demand-related channels. Moreover, analysts increase their discussion of both developments already affecting firms and changes expected to materialize in the future, with the larger effects generally concentrated in the anticipated future component.

5.2.3. Heterogeneous Effects by Firms' Exposure to Environmental Risk

Firms differ in how environmental concerns affect their expected cash flows. Pollution-intensive firms may bear higher costs as environmental regulation tightens or demand shifts away from pollution-intensive products, whereas firms providing cleaner technologies or products may benefit from these same changes. We therefore examine

whether the effect of the monitoring program varies with firms' exposure to environmental risks. We instruct *DeepSeek-Reasoner* to read the business description in each firm's 2011 MD&A and classify the firm as brown, green, or neutral. Brown firms are expected to be adversely affected by heightened environmental concerns, green firms are expected to benefit, and neutral firms are those for which the net effect is ambiguous. This procedure classifies 149 firms as brown (*Brown Firm*), 184 as green (*Green Firm*), and the remaining 1,127 firms as neutral (*Neutral Firm*). Based on a manual classification of 100 randomly selected firms, the model achieves 98% accuracy for brown firms and 99% for green firms, with corresponding F1 scores of 93.3% and 97.6%. We provide additional details on the LLM's performance in Internet Appendix B.

Table 6 reports results separately for analyst reports covering *Brown*, *Green*, and *Neutral* firms, and Panel (b) of Figure 2 presents the corresponding event-study estimates. Following the introduction of monitoring, treated analysts are 6.1 percentage points more likely to discuss air pollution in reports on green firms and 5.0 percentage points more likely to do so in reports on brown firms, relative to control analysts covering the same firms in the same period. These estimates represent increases of approximately 73% and 185%, respectively, relative to the pre-treatment means. By contrast, pollution discussions for neutral firms increase by only 1.3 percentage points, significantly less than the increases for green and brown firms. The event-study estimates show no evidence of differential pre-treatment trends in *Air Pollution Discussed* for any of the three groups.

We also examine whether the increase in attention to specific types of environmental risk varies across firms. Building on the results in Section 5.2.2, Panels A and B of Table A4 show that treated analysts' discussions of both regulatory risks and preference-related factors increase significantly more for brown and green firms than for neutral firms.

As a robustness test, we use an alternative, government-designated measure of firms' exposure to environmental risk that does not rely on the language model. We identify high-emitting firms using the Environmental Survey and Reporting (ESR) database administered by China's Ministry of Environmental Protection, which identifies establishments responsible for the bulk of pollution in each county-year. We classify firms appearing in the database in the year before the monitoring program as brown and all other firms as not brown. Table A3 shows that our inferences are similar using this alternative classification: the effects of the monitoring program are concentrated among government-designated brown firms.

Taken together, these results show that the increase in analysts' pollution-related discussion following the monitoring rollout is concentrated in reports on firms for which environmental issues are more financially material. Thus, heightened pollution salience does not lead analysts to increase environmental discussion uniformly across the firms they

cover; instead, analysts increase such discussion disproportionately in reports on green and brown firms, whose expected cash flows are more exposed to changes in environmental regulation and preferences.

5.3. Impacts on Firm Stock Prices and Their Persistence

5.3.1. Stock Market Reaction to Analyst Reports

We next examine whether the changes in analyst reports documented above are reflected in the stock prices of the firms they cover. If heightened pollution salience changes analysts' assessments of financially material environmental risks, reports issued by treated analysts should elicit more negative market reactions for brown firms and more positive reactions for green firms. In contrast, we expect little change in market reactions for environmentally neutral firms, whose expected cash flows are less exposed to environmental regulation and shifts in consumer preferences.

We measure the market reaction as the 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 7 presents the results. Panel (c) of Figure 2 presents the corresponding event-study estimates for the full sample, while Panel (d) presents the estimates separately by firms' exposure to environmental risk.[22]

In the full sample, we find no significant average change in market reactions to reports issued by treated analysts relative to control analysts (Column 1). This is consistent with the opposing predicted effects for green and brown firms offsetting one another in the aggregate. The cross-sectional results, however, reveal systematic differences by firms' environmental exposure. For brown firms, market reactions to reports issued by treated analysts become significantly more negative relative to reactions to reports by control analysts covering the same firms in the same period. For green firms, market reactions become significantly more positive, while we find no significant change for neutral firms. In economic terms, reports issued by treated analysts generate market reactions that are 0.834 percentage points more positive for green firms and 1.185 percentage points more negative for brown firms. These effects correspond to 17.7% and 26.0% of the standard deviation of *Market Reaction*, respectively.[23]

[22] The sample size in Table 7 is smaller than that in Table 4 because we exclude analyst reports issued on the same day as the firm's annual earnings announcement or a mandatory earnings preannouncement, to avoid capturing market reactions attributable to those disclosures rather than to the analyst report. The Shanghai and Shenzhen stock exchanges require listed firms to issue an earnings preannouncement when they expect (i) a loss, (ii) a turnaround from a loss to a profit, or (iii) an increase or decrease in net profit of at least 50% relative to the prior year. For annual earnings, such preannouncements must be issued within one month after the fiscal year-end, i.e., by January 31 (Shanghai Stock Exchange, 2006; Shenzhen Stock Exchange, 2006).

[23] 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

Panel (d) of Figure 2 presents the corresponding event-study estimates separately for green, brown, and neutral firms. For brown firms, market reactions become significantly more negative in the first quarter following treatment and subsequently attenuate. This pattern is consistent with an initial repricing of environmental risk: once heightened pollution salience leads analysts to incorporate these risks into their reports and investors respond to this information, subsequent reports need not generate equally large valuation revisions. For green firms, the positive market reaction emerges more gradually and is concentrated in the second post-treatment quarter. This delayed response is consistent with differences in the information environment across green and brown firms. In particular, using pre-treatment data, we find that green firms are significantly smaller, younger, and followed by fewer analysts than brown firms (untabulated), suggesting that the valuation implications of heightened environmental salience may take longer to be incorporated into prices for these firms.

The pre-treatment estimates show no systematic differential trend in market reactions. One exception is the estimate for brown firms four quarters before treatment, which is positive and statistically significant. Because the estimates in the subsequent pre-treatment quarters are close to zero and the post-treatment effect is negative, this isolated coefficient does not appear to reflect a continuation of a pre-existing trend into the treatment period.

We conduct a back-of-the-envelope calculation to gauge the aggregate economic magnitude of these report-level price responses. For green firms, the estimated 0.834% market reaction implies a cumulative market-value increase of approximately $35 billion across reports issued by treated analysts. Specifically, treated analysts issue 1,807 reports on green firms during the post-implementation period, and these firms have an average market value of $2.35 billion as of the end of 2011, the year before the monitoring program. Applying the estimated market reaction to the average market value and number of reports yields $0.834\% \times \$2.35 \text{ billion} \times 1{,}807 \approx \$35 \text{ billion}$. For brown firms, treated analysts issue 1,584 reports, and these firms have an average pre-program market value of $7.43 billion. The corresponding calculation yields a cumulative market-value decrease of approximately $139 billion: $-1.185\% \times \$7.43 \text{ billion} \times 1{,}584 \approx -\$139 \text{ billion}$.

Thus, across reports issued by treated analysts during our roughly two-year post-monitoring sample period, the estimated price responses imply approximately $35 billion in cumulative gains for green firms and $139 billion in cumulative losses for brown firms. The sum of the absolute values of these effects, approximately $174 billion, is equivalent to about 5% of the $3.4 trillion total capitalization of China's stock market at

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

the end of 2011.[24] These magnitudes suggest that the increased incorporation of environmental risks into analyst reports can have economically meaningful consequences for stock prices.

5.3.2. Stock Return Reversal and Price Efficiency

We next examine whether the stock price reactions documented above reflect more persistent incorporation of environmental risk or temporary overreaction induced by heightened salience. Prior research shows that salient information can receive disproportionate weight, generating temporary price distortions that subsequently reverse (e.g., Afrouzi et al., 2023; deHaan et al., 2025). If heightened pollution salience causes analysts or investors to place excessive weight on environmental risks, the initial stock price response to treated analysts' reports should be followed by returns in the opposite direction. We therefore examine whether the initial market reaction to an analyst report subsequently reverses.

Specifically, we estimate a modified version of Equation 2 using post-report buy-and-hold abnormal returns over the following 12 months as the dependent variable.[25] We augment the specification with interactions among *Treated*, *Post*, and *Market Reaction*, where *Market Reaction* is the three-day abnormal return around the analyst report. If the initial price response subsequently reverses, more positive initial reactions should predict more negative subsequent returns, and vice versa. Our primary interest is therefore whether this reversal relation becomes more negative for reports issued by treated analysts after the monitoring program is introduced.

Table 8 presents the results. Across all specifications, including the full sample and subsamples based on firms' environmental risk exposure, we find no evidence of increased return reversal following the monitoring program. In particular, the relation between the initial market reaction and subsequent returns does not become significantly more negative for reports issued by treated analysts relative to control analysts. Thus, the price reactions documented in Section 5.3.1 do not appear to reflect temporary overreaction to heightened pollution salience. Instead, their persistence is consistent with environmental risks becoming more durably incorporated into stock prices.

We next provide complementary evidence on whether the monitoring program improves

[24] Because a given firm may be covered by multiple analyst reports, these calculations capture the cumulative magnitude of report-level market-value responses rather than a one-time change in aggregate stock market capitalization. We obtain the estimate of China's total stock market capitalization from the World Bank, World Development Indicators, available at https://data.worldbank.org/indicator/CM.MKT.LCAP.CD?locations=CN.

[25] We use a 12-month post-report horizon to allow sufficient time for subsequent firm disclosures, including earnings announcements, to correct any temporary mispricing. Table A5 in the Internet Appendix shows that our inferences are robust to using a one-month horizon.

price efficiency. If reports issued by treated analysts cause information about the cash-flow implications of environmental risk to be incorporated into prices earlier, less information should remain to be incorporated at subsequent earnings announcements, resulting in smaller stock price reactions around those announcements (Chen et al., 2022). To test this prediction, we construct a firm-level measure of exposure to treated analysts. For each firm-year-quarter, *Treated Analyst Ratio* equals the proportion of analysts covering the firm at the beginning of the quarter who are located in cities in which the monitoring program has already been implemented. We then examine whether firms with greater exposure to treated analysts experience smaller market reactions around subsequent earnings announcements. We measure *Market Reaction to Earnings Announcement* as the absolute value of the cumulative abnormal return over the three-day window centered on the quarterly earnings announcement date.

Table 9 reports the results. We find that a higher share of treated analysts is associated with significantly smaller 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 *Treated Analyst Ratio* is associated with a reduction in the earnings-announcement market reaction of approximately 16–17% relative to the mean for green and brown firms.[26]

Collectively, these findings indicate that the monitoring program facilitates the incorporation of environmental risk into stock prices. The absence of return reversals suggests that the initial market reactions do not reflect temporary overreaction, while the smaller reactions around subsequent earnings announcements indicate that information that would otherwise have been incorporated at those announcements is reflected in prices earlier. Overall, the evidence is consistent with heightened pollution salience improving the timeliness with which financially material environmental risks are incorporated into stock prices.

5.4. Mechanisms

Our analyses thus far show that the monitoring program increases analysts' attention to pollution-related risks and that investors respond more negatively to treated analysts' reports on brown firms and more positively to their reports on green firms. We next examine how heightened pollution salience changes analysts' information acquisition and assessments

[26]Table A6 in the Internet Appendix examines the profitability of stock recommendations, measured following Chen et al. (2022). This measure captures 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 findings provide additional evidence that analysts' recommendations become more informative about future returns following the monitoring program, particularly for firms whose values are more exposed to environmental risks.

of the firms they cover. First, we examine whether treated analysts devote greater effort to acquiring firm-specific information, using corporate site visits as a proxy for information acquisition. Second, we examine how analysts revise their quantitative assessments, including earnings forecasts, stock recommendations, target prices, and report tone.

5.4.1. Site Visits

Heightened pollution salience may lead analysts to devote greater effort to understanding how environmental risks affect the firms they cover. We examine this information-acquisition channel using corporate site visits. Prior research shows that site visits allow analysts to gather soft information about firms' operations, interact directly with management, and assess firm-specific risks that may be difficult to infer from public disclosures (e.g., Cheng et al., 2016; Chen et al., 2022).[27] If heightened pollution salience motivates analysts to acquire additional information about firms' environmental exposure, we expect treated analysts to increase their site visits particularly for green and brown firms, for which environmental risks are more likely to be financially material.

To test this prediction, we construct a firm-year-quarter-analyst level sample and estimate a specification analogous to Equation 2, with *Site Visit*, an indicator equal to one if the analyst visits the covered firm during the quarter, as the dependent variable. Panel A of Table 10 presents the results, while Panels (e) and (f) of Figure 2 present the corresponding event-study estimates for the full sample and the heterogeneity tests, respectively. Consistent with our prediction, treated analysts significantly increase their site visits to both green and brown firms following the introduction 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 149% for brown firms relative to their pre-program means.

We next provide complementary, albeit more suggestive, evidence on whether air pollution is actually discussed during these site visits. We view this evidence as suggestive because the underlying data begin in 2012, after the first cohort had already received treatment. In 2012, the Shenzhen Stock Exchange required listed firms to disclose records of communications between company representatives and participants during corporate site visits, and these disclosures are limited before 2012, when disclosing detailed records was voluntary. To measure pollution-related discussion, we construct a variable analogous to our *Air Pollution Discussed* measure by applying *DeepSeek-R1* to the question-and-answer portion of these site-visit records. For each visit, we also define *Treated Analyst Ratio (Site Visits)* as the proportion of attending analysts based in cities that had already

[27] Firms listed on the Shenzhen Stock Exchange 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 the identity of the visiting analyst or institution. We obtain these data from the CNRDS database.

implemented the monitoring program. We then estimate firm-visit level regressions using observations from 2012Q1–2013Q3. Panel B of Table 10 presents the results. A higher share of treated analysts attending a visit is associated with a significantly greater likelihood that air pollution is discussed, and this relation is concentrated among green and brown firms.

Taken together, these findings suggest that heightened pollution salience not only changes how analysts assess the firms they cover but also induces them to acquire additional firm-specific information, particularly for firms whose values are more exposed to environmental risks.

5.4.2. Analyst Quantitative Outputs

We next examine whether heightened pollution salience affects analysts' quantitative assessments of the firms they cover, including earnings forecasts, stock recommendations, target prices, and report tone. Building on our earlier evidence that treated analysts devote greater attention to regulatory and demand-related environmental risks, we expect these assessments to become less favorable for brown firms and more favorable for green firms following the introduction of monitoring. In particular, treated analysts should issue more pessimistic earnings forecasts, lower target prices, less favorable stock recommendations, and more negative reports for brown firms, with the opposite pattern for green firms. We expect little change for environmentally neutral firms, for which environmental risks are less likely to be financially material.

To test these predictions, we estimate Equation 2 using analyst outputs as the dependent variables. We examine four measures: (i) *EPS Forecast*, defined as the analyst's annual earnings-per-share forecast scaled by the firm's stock price at the beginning of the fiscal year and multiplied by 100; (ii) *Recommendation*, an ordinal variable ranging from 1 to 5, with higher values indicating more favorable recommendations (1 = strong sell; 5 = strong buy); (iii) *Target Price*, defined as the ratio of the analyst's target price 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 the report, scaled by the total number of positive and negative words.

Table 11 presents the results. Figure 2 presents the corresponding event-study estimates for *EPS Forecast* (Panels (g) and (h)), *Recommendation* (Panels (i) and (j)), *Target Price* (Panels (k) and (l)), and *Report Tone* (Panels (m) and (n)); within each pair, the first panel presents the full-sample estimates and the second presents the heterogeneity estimates. Panel A of Table 11 shows that, for the average firm, the quantitative outputs of treated analysts do not differ significantly from those of control analysts. Panel B, however, reveals pronounced heterogeneity by firms' environmental exposure. Treated analysts issue more favorable assessments of green firms and less favorable assessments of brown firms relative to

control analysts covering the same firms in the same period, while we observe little change for environmentally neutral firms.

For green firms, the estimates in Panel B indicate that treated analysts' *EPS Forecasts* increase by 6.4% relative to the pre-program mean. Similarly, treated analysts' *Recommendations* and *Target Prices* increase by 3.5% and 11.4%, respectively, while *Report Tone* increases by 28.4% of its pre-program standard deviation.[28] The effects for brown firms are of the opposite sign. Treated analysts' *EPS Forecasts*, *Recommendations*, and *Target Prices* are 7.8%, 3.8%, and 9.9% lower, respectively, relative to their pre-program means, while *Report Tone* declines by 22.3% of its pre-program standard deviation. By contrast, we find no statistically significant or economically meaningful changes in these outputs for environmentally neutral firms.

The corresponding event-study estimates in Panels (h), (j), (l), and (n) of Figure 2 broadly reinforce these findings: following treatment, analyst assessments of green and brown firms diverge in the predicted directions, while the estimates for neutral firms remain close to zero. The timing of the recommendation effects also closely parallels the market-reaction results documented in Section 5.3.1. For brown firms, treated analysts issue significantly less favorable recommendations in the first post-treatment quarter, when market reactions to their reports also become significantly more negative. By the second post-treatment quarter, the recommendation effect attenuates, even though treated analysts continue to issue lower earnings forecasts and target prices. This pattern is consistent with an initial downward repricing: once stock prices adjust to the less favorable assessment of brown firms' fundamentals, the expected-return implications of that assessment, and hence the effect on stock recommendations, need not persist. For green firms, the recommendation effect instead becomes more pronounced in the second post-treatment quarter, coinciding with the delayed positive market reaction documented in Section 5.3.1. This parallel timing is consistent with our earlier interpretation of the more gradual incorporation of environmental information into the valuations of green firms.

5.4.3. Forecast Accuracy

We next examine whether heightened pollution salience improves analysts' earnings forecast accuracy. This test complements the site-visit evidence above: if greater salience induces analysts to acquire and process additional firm-specific information, their forecasts may become more accurate. Forecast accuracy also helps distinguish this information-based interpretation from a behavioral bias in which analysts place excessive weight on pollution.

[28] We measure economic magnitudes by comparing the coefficient estimate for *Treated* × *Post* with the pre-program mean of the dependent variable for *EPS Forecast*, *Recommendation*, and *Target Price*. Because *Report Tone* can take both positive and negative values, we instead scale its coefficient by the pre-program standard deviation of *Report Tone*.

If heightened salience directs attention toward financially material environmental risks, forecast accuracy should improve; by contrast, accuracy may remain unchanged or decline if attention to pollution crowds out other value-relevant information.

Following prior research (e.g., Dong et al., 2021), we measure *Forecast Accuracy* as negative one multiplied by $|Analyst\ EPS\ Forecast - Actual\ EPS|$ divided by $|Actual\ EPS|$, such that higher values indicate greater accuracy. We estimate Equation 2 using *Forecast Accuracy* as the dependent variable. Table 12 presents the results, while Panels (o) and (p) of Figure 2 present the corresponding event-study estimates for the full sample and the heterogeneity tests, respectively. We find that forecast accuracy significantly improves for treated analysts in the full sample and, consistent with our earlier results, that this improvement is concentrated among green and brown firms; we find no significant change for neutral firms. In economic terms, the estimated improvement corresponds to approximately 3% of the magnitude of the pre-program mean for the full sample, 12% for green firms, and 14% for brown firms. These findings are consistent with heightened pollution salience directing analysts' attention toward value-relevant environmental information rather than causing them to overweight pollution at the expense of other information.

5.5. Additional Analyses and Robustness Tests

We conduct several additional analyses, reported in the Internet Appendix, to assess the robustness of our findings and address alternative explanations. First, we implement an alternative identification strategy that does not rely on the staggered timing of the monitoring program. Specifically, we use a static DiD design based on Chinese firms that are cross-listed in foreign markets and are covered by both mainland Chinese and foreign analysts. Analysts based in mainland China constitute the treated group, while analysts located outside mainland China (e.g., in the U.S. or Hong Kong) constitute the control group. We exclude the eight quarters spanning the first adoption quarter (2012Q1) through the final adoption quarter (2013Q4) and compare changes in analyst outcomes between the 2008–2011 pre-period and the 2014–2017 post-period. Because foreign analysts are not locally exposed to pollution conditions or the monitoring rollout in mainland China, this design compares analysts with differential exposure to pollution salience while holding constant the firms they cover.[29] The results, reported in Panels A–F of Table A7, are consistent with those from our baseline specification.

[29]As noted earlier, geographic proximity may confer an information advantage on analysts based in mainland China relative to those located in the U.S. or Hong Kong. Our identification, however, relies on changes in analyst behavior between the pre- and post-periods. Time-invariant differences in information associated with geographic proximity are absorbed by the Analyst × Firm fixed effects and therefore do not affect our inferences.

Second, we conduct several cross-sectional tests that provide additional evidence on the salience mechanism. Table A8 reports these results. In Columns 1 and 2, the effect of the monitoring program is weaker for analysts located in Beijing, where the U.S. embassy provided pollution information prior to the nationwide monitoring program.[30] We also find stronger effects among younger analysts (Columns 3 and 4), consistent with survey evidence that younger individuals exhibit greater concern about environmental issues and are more likely to seek information and engage with such issues (e.g., Tyson et al., 2021; Poortinga et al., 2023). Finally, the effects are stronger among star analysts (Columns 5 and 6), consistent with analysts with greater ability or stronger incentives to process value-relevant information responding more strongly when environmental risks become salient. Collectively, these cross-sectional patterns are consistent with the monitoring program operating through changes in attention to pollution-related information.

Third, we verify that our results are robust to alternative measures and specifications. Table A9 shows that our inferences are unchanged when we replace our LLM-based measure of pollution-related discussion with a dictionary-based measure following Lin et al. (2024), who use a word-embedding model to construct a pollution-disclosure dictionary. We also re-estimate our heterogeneity tests in a single regression using triple interactions rather than estimating separate regressions for green, brown, and neutral firms. Table A10 shows that our inferences are unchanged under this alternative specification.

Fourth, we examine the sensitivity of our findings to alternative sample restrictions and estimation choices. Our results are largely robust to excluding reports issued by analysts located in the same city as the covered firm (Table A11); restricting the sample to firms located in cities in which monitoring had not yet been implemented during our main sample period (Table A12); clustering standard errors at the city level (Table A13); and including additional controls for analyst experience and the length of the analyst–firm relationship (Table A14).

Fifth, we consider an alternative explanation in which the monitoring program improves analysts' decision-making by reducing their exposure to adverse environmental conditions rather than by increasing the salience of environmental risk. Prior research shows that poor ambient conditions, including air pollution and adverse weather, can impair the information processing, judgment, and performance of investors and financial analysts (deHaan et al., 2017; Huang et al., 2020; Li et al., 2020; Dong et al., 2021; Li et al., 2021).

[30]The U.S. Embassy in Beijing reported hourly $PM_{2.5}$ levels to inform U.S. citizens in China. Although access to the primary dissemination channel, Twitter, was restricted in China, analysts residing in Beijing may nevertheless have had greater prior exposure to pollution information through alternative channels. Consistent with this interpretation, the monitoring program has a weaker effect on pollution-related discussion among analysts residing in Beijing.

Because access to real-time pollution information can induce defensive behaviors that reduce pollution exposure, the monitoring program could improve analysts' health or cognitive functioning and, in turn, their on-the-job performance. This explanation, however, is difficult to reconcile with the cross-sectional pattern of our findings. A general improvement in cognitive functioning would not naturally predict that the effects are concentrated among green and brown firms, for which environmental risks are financially material, while remaining largely absent for environmentally neutral firms. This pattern is more consistent with monitoring increasing analysts' attention to environmental risk than with a general improvement in cognitive functioning.

Finally, our findings are robust to sequentially excluding individual treatment cohorts (untabulated). We also obtain similar results from a conventional staggered DiD specification that allows both earlier- and later-treated analysts to serve as controls, rather than restricting the control group to not-yet-treated analysts.[31] Overall, these additional analyses reinforce our interpretation that the observed changes in analyst behavior and market outcomes reflect heightened pollution salience rather than features of our particular measurement choices, sample construction, or empirical specification.

6. Conclusion

This paper examines whether ambient environmental monitoring affects how financially sophisticated market participants, namely financial analysts, incorporate environmental risk into firm valuations. We document three main findings. First, when pollution monitoring is introduced in an analyst's city of residence, the analyst becomes substantially more likely to discuss air pollution in research reports relative to not-yet-treated analysts covering the same firm in the same period. This increase more than doubles the pre-treatment frequency of pollution-related discussion and is not accompanied by a corresponding increase in discussions of unrelated non-financial topics, such as human or social capital. Moreover, treated analysts primarily increase their discussion of transition risks, particularly regulatory risks and changes in consumer demand, and the increase encompasses both developments already affecting firms and changes anticipated to arise in the future.

Second, these changes in analysts' attention are reflected in stock prices. Market reactions to reports issued by treated analysts become more negative for brown firms and more positive for green firms, with little corresponding change for neutral firms. These price responses do not subsequently reverse. Moreover, when a larger share of the analysts covering a green or brown firm has been treated, subsequent earnings announcements generate smaller stock-price reactions, suggesting that information that would otherwise be

[31] The untabulated results are available from the authors upon request.

incorporated at the earnings announcement is reflected in prices earlier. Collectively, these findings are inconsistent with temporary salience-induced overreaction and are instead consistent with heightened pollution salience improving the timeliness with which financially material environmental risks are incorporated into stock prices.

Third, we examine how heightened pollution salience changes analysts' information acquisition and assessments of the firms they cover. Treated analysts issue more pessimistic earnings forecasts, lower target prices, less favorable stock recommendations, and reports with more negative tone for brown firms, while exhibiting the opposite pattern for green firms. We find little corresponding change for environmentally neutral firms. Heightened salience also affects analysts' information production: treated analysts increase corporate site visits to green and brown firms, and their earnings forecasts become more accurate. Together, these findings suggest that greater pollution salience not only changes analysts' assessments of firms but also induces them to acquire additional firm-specific information about how environmental risks affect future cash flows.

Our findings highlight a broader role for environmental information policy. For concerns about firms' environmental impacts to influence capital allocation through financial markets, those concerns must ultimately be incorporated into asset prices. The monitoring program we study was designed primarily to improve transparency and public awareness of pollution, rather than to influence financial markets. Nevertheless, by making environmental risks more salient to financially sophisticated intermediaries, the program changes analysts' information acquisition and valuation assessments and generates economically meaningful stock-price responses. More broadly, our evidence suggests that the effects of public information provision depend not only on whether information is available, but also on whether it attracts the attention of market participants and induces them to investigate its implications for firms' future cash flows. Environmental monitoring can therefore affect financial markets even without directly regulating firms' emissions or changing their disclosure obligations, providing a channel through which public information policy can facilitate the incorporation of environmental risks into asset prices.

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.

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.

Barber, Brad M., Xing Huang, Terrance Odean, and Christopher Schwarz, 2022, Attention-induced trading and returns: Evidence from Robinhood users, *The Journal of Finance* 77, 3141–3190.

Barber, Brad M., and Terrance Odean, 2008, All that glitters: The effect of attention and news on the buying behavior of individual and institutional investors, *The Review of Financial Studies* 21, 785–818.

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, 3677–3754.

Bordalo, Pedro, Nicola Gennaioli, and Andrei Shleifer, 2012, Salience theory of choice under risk, *Quarterly Journal of Economics* 127, 1243–1285.

Bordalo, Pedro, Nicola Gennaioli, and Andrei Shleifer, 2013, Salience and asset prices, *American Economic Review: Papers & Proceedings* 103, 623–628.

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

Bourveau, Thomas, and Kelvin K. Law, 2021, Do disruptive life events affect how analysts assess risk? Evidence from deadly hurricanes, *The Accounting Review* 96, 121–140.

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.

Correa, Ricardo, Ai He, Christoph Herpfer, and Ugur Lel, 2026, The rising tide lifts some interest rates: climate change, natural disasters, and loan pricing, *The Journal of Finance* 81, 2933–2984.

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.

Frydman, Cary, and Baolian Wang, 2020, The impact of salience on investor behavior: Evidence from a natural experiment, *The Journal of Finance* 75, 229–276.

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* 15, 281–299.

Hartzmark, Samuel M., 2015, The worst, the best, ignoring all the rest: The rank effect and trading behavior, *The Review of Financial Studies* 28, 1024–1059.

Hartzmark, Samuel M., and Kelly Shue, 2018, A tough act to follow: Contrast effects in financial markets, *The Journal of Finance* 73, 1567–1613.

Hong, Harrison, and Jeffrey D. Kubik, 2003, Analyzing the analysts: Career concerns and biased earnings forecasts, *The Journal of Finance* 58, 313–351.

Huang, Jiekun, Nianhang Xu, and Honghai Yu, 2020, Pollution and performance: Do investors make worse trades on hazy days?, *Management Science* 66, 4455–4476.

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.

Malmendier, Ulrike, Demian Pouzo, and Victoria Vanasco, 2020, Investor experiences and financial market dynamics, *Journal of Financial Economics* 136, 597–622.

Mikhail, Michael B., Beverly R. Walther, and Richard H. Willis, 1999, Does forecast accuracy matter to security analysts?, *The Accounting Review* 74, 185–200.

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

Petersen, Mitchell A, 2009, 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.

Shanghai Stock Exchange, 2006, Rules governing the listing of stocks on the Shanghai Stock Exchange (2006 revision), http://www.ce.cn/securities/stock/ywgc/gsyw/200605/19/t20060519_7015920_3.shtml.

Shenzhen Stock Exchange, 2006, Guidelines on information disclosure by listed companies no. 1: Earnings preannouncements and preliminary earnings reports, https://www.szse.cn/disclosure/notice/general/t20060710_499625.html.

Tomar, Sorab, 2023, Greenhouse gas disclosure and emissions benchmarking, *Journal of Accounting Research* 61, 451–492.

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. Variable Definitions

Variable	Definition	Data Source
Awareness of Air Pollution Tests [Table 3]		
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. 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 treated cities implement 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*
Transition Risks Discussed	An indicator variable that equals one if the analyst's report discusses any transition risk, defined as the risk to a firm's cash flows arising from the economy's adjustment toward lower emissions. We measure such risk using analysts' discussion of environmental regulation (e.g., an increase in carbon taxes, reduction in emission caps), shifts in consumer preferences (e.g., heightened pollution and climate concern tilts product-market demand away from pollution-intensive goods and toward greener alternatives), and stakeholder responses (e.g., investors acting on environmental concerns restrict a polluting firm's financing), and set this indicator to one if at least one of *Regulatory Risks Discussed*, *Preference-related Factors Discussed*, or *Stakeholder Risks Discussed* equals one.	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*

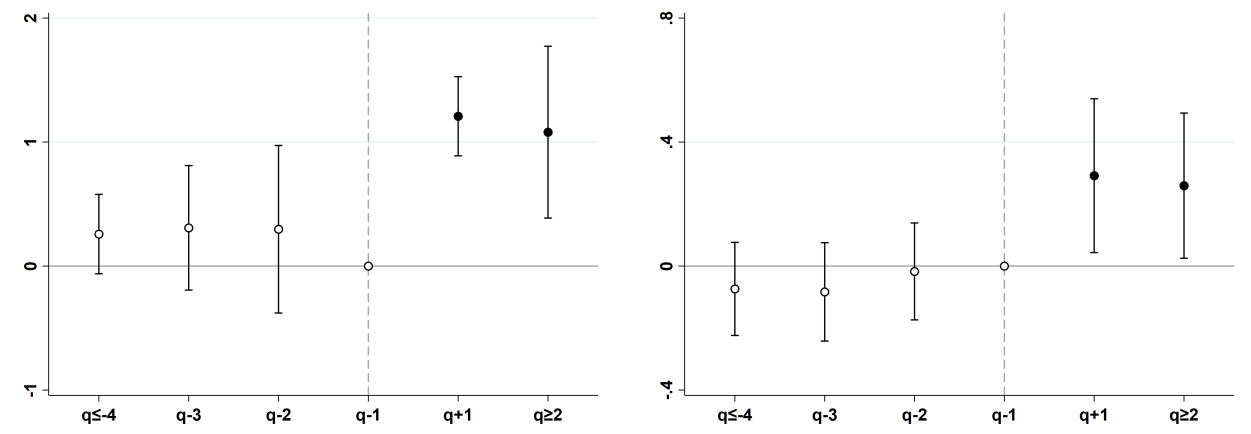
Preference-related Factors Discussed	An indicator variable that equals one if the analyst's report discusses changes in customer demand or competitive dynamics driven by concerns about pollution or climate change. We use *DeepSeek-R1* to classify these discussions based solely on the text of the analyst 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*
Stakeholder Risks Discussed	An indicator variable that equals one if the analyst's report discusses reactions by investors, the firm's supply chain, or other stakeholders to the firm's pollution- or climate-related actions. 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., a higher cost of capital for high-polluting firms) or positive consequences (e.g., an improved ability to attract and retain talent for green firms).	CnOpenData & *DeepSeek-R1*
Current Regulatory Risks Discussed	An indicator variable that equals one if the analyst's report discusses regulatory risks related to environmental policies that are already in place or already taking effect (e.g., existing emissions caps, a carbon price or tax currently in force, environmental penalties already imposed).	CnOpenData & *DeepSeek-R1*
Future Regulatory Risks Discussed	An indicator variable that equals one if the analyst's report discusses regulatory risks related to environmental policies that are anticipated or expected but not yet binding (e.g., proposed policies, an expected tightening of emissions rules, a prospective carbon tax).	CnOpenData & *DeepSeek-R1*
Current Preference-related Factors Discussed	An indicator variable that equals one if the analyst's report discusses a change in customer demand or competitive dynamics, driven by concerns about pollution or climate change, that has already been observed or is already affecting the firm.	CnOpenData & *DeepSeek-R1*
Future Preference-related Factors Discussed	An indicator variable that equals one if the analyst's report discusses a change in customer demand or competitive dynamics, driven by concerns about pollution or climate change, that is anticipated or expected to develop.	CnOpenData & *DeepSeek-R1*
Heterogeneity Variables [Table 6]		
Green Firm	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 obtained from the websites of the Shanghai and Shenzhen Stock Exchanges & *DeepSeek-Reasoner*

Brown Firm	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 obtained from the websites of the Shanghai and Shenzhen Stock Exchanges & *DeepSeek-Reasoner*
Neutral Firm	An indicator variable that equals one if the firm is neither a *Green Firm* nor a *Brown Firm*.	
Market Reaction [Table 7]		
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.	CSMAR
Return Reversal [Table 8]		
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-month period after the analyst report date.	CSMAR
Stock Price Efficiency [Table 9]		
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 number 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.	The program's rollout dates were manually collected from news media and city yearbooks & CNRDS
Site Visits [Table 10]		
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.	CNRDS

Pollution Discussed During Site Visits	An indicator variable that equals one if air quality is discussed during the question-and-answer portion of the site visit, and zero otherwise. This variable is derived by instructing a generative large language model (*DeepSeek-R1*) to focus exclusively on the content of discussions during site visits and classify whether they discuss air quality issues as defined by the Sustainability Accounting Standards Board (SASB).	CNRDS & *DeepSeek-R1*
Treated Analyst Ratio (Site Visits)	The fraction of analysts attending the visit who are based in cities that had already implemented the monitoring program as of the visit date. We standardize this measure to have a mean of zero and a standard deviation of one.	The program's rollout dates were manually collected from news media and city yearbooks & CNRDS
Analyst Outputs [Table 11]		
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). We obtain EPS forecasts from CNRDS and stock prices from CSMAR.	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. We extract target price forecasts from the text of the analyst reports and obtain stock prices from CSMAR.	CnOpenData & CSMAR
Report Tone	*Report Tone* 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. We translate each report from Chinese into English and then apply the Loughran-McDonald dictionary (Loughran and McDonald, 2011) to identify positive and negative words.	CnOpenData
Forecast Accuracy [Table 12]		
Forecast Accuracy	Negative one multiplied by $\lvert Analyst\ EPS\ Forecast_{ij} - Actual\ EPS_i \rvert$ divided by $\lvert Actual\ EPS_i \rvert$, where $Analyst\ EPS\ Forecast_{ij}$ is analyst j's EPS forecast issued for firm i, and $Actual\ EPS_i$ is firm i's actual EPS. Larger values indicate greater forecast accuracy.	CNRDS

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

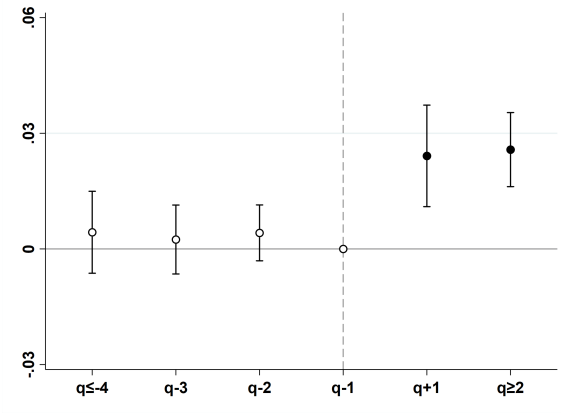
(a) ***News Coverage*** (b) ***Internet Search***



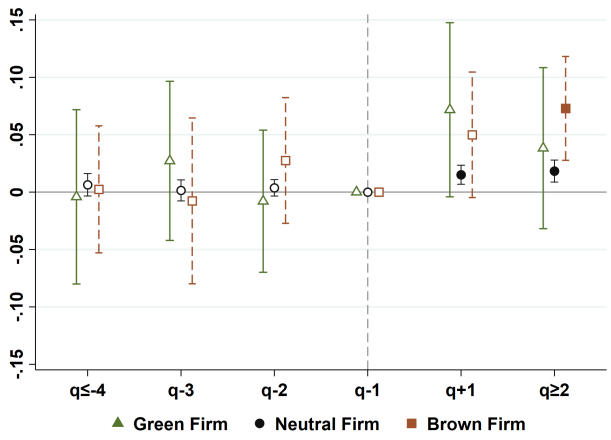
Notes: This figure presents evidence of the effect of the monitoring program on the awareness about air pollution for quarters before and after the monitoring program's implementation. The estimated coefficients are obtained from estimating Equation 1 modified by replacing *Post* with a set of indicator variables for quarters before and after the program's implementation (except the quarter immediately before implementation *q-1*, which is the base quarter). The endpoint indicators $q \leq -4$ and $q \geq 2$ pool all quarters four or more quarters before and two or more quarters after implementation, respectively. 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 $\times$ Year level. Each shaded (unshaded) circle on the graph represents a significant (insignificant) regression coefficient.

Figure 2. Event-study figures

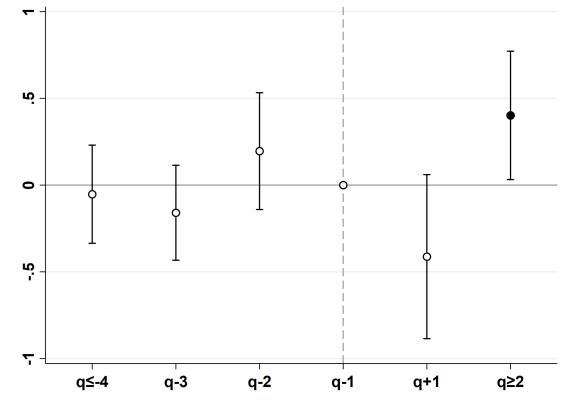
(a) *Air Pollution Discussed* - Full sample



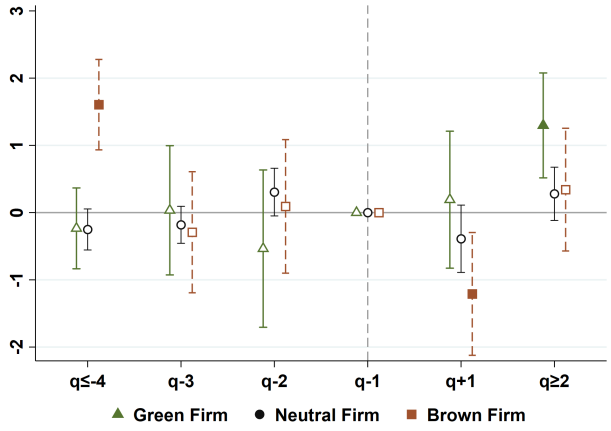
(b) *Air Pollution Discussed* - Heterogeneity tests



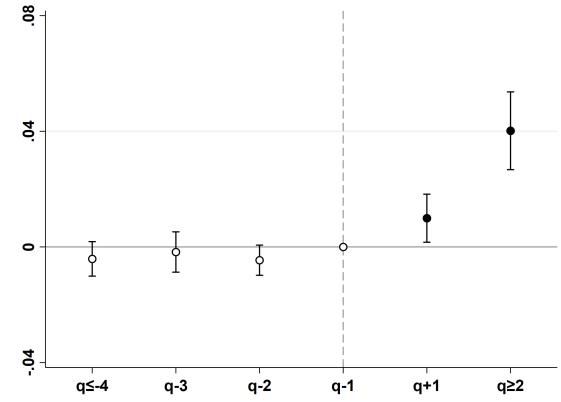
(c) *Market Reaction (%)* - Full sample



(d) *Market Reaction (%)* - Heterogeneity tests



(e) *Site Visit* - Full sample



(f) *Site Visit* - Heterogeneity tests

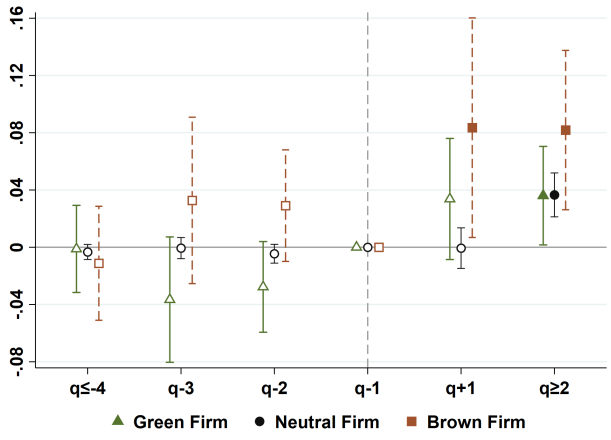
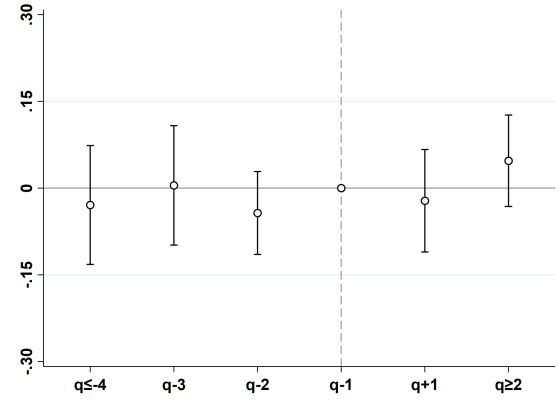
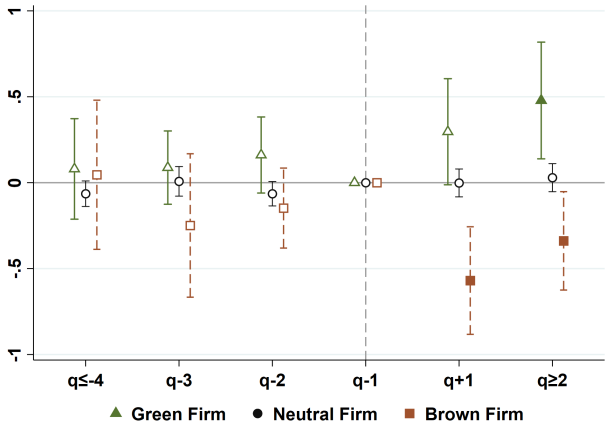


Figure 2 (Continued)

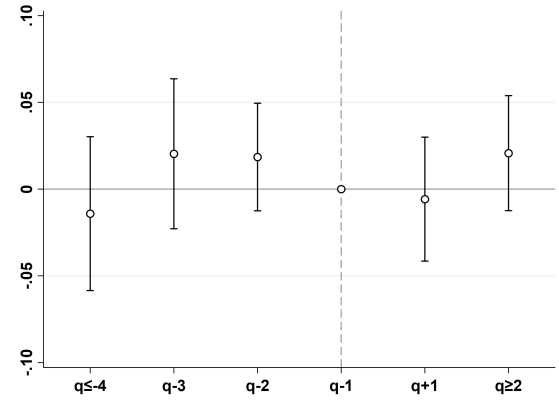
(g) *EPS Forecast (%)* - Full sample



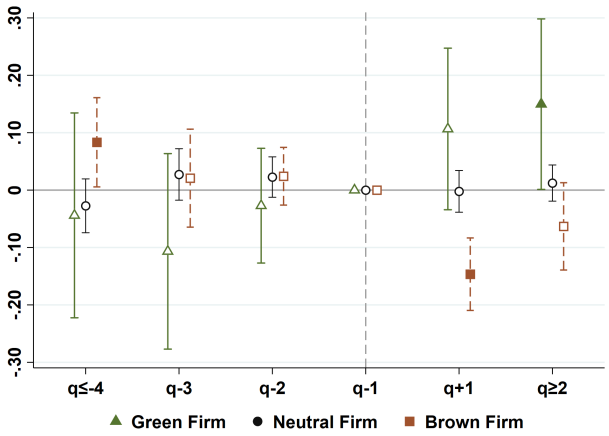
(h) *EPS Forecast (%)* - Heterogeneity tests



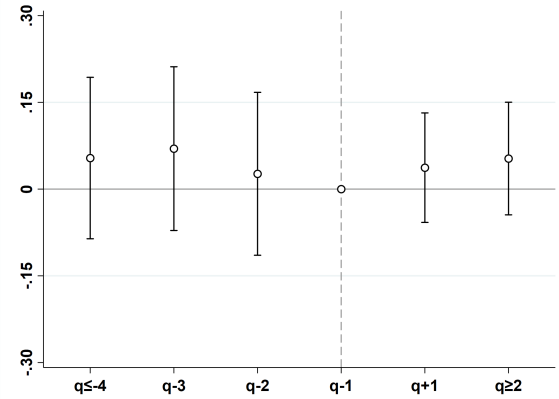
(i) *Recommendation* - Full sample



(j) *Recommendation* - Heterogeneity tests



(k) *Target Price* - Full sample



(l) *Target Price* - Heterogeneity tests

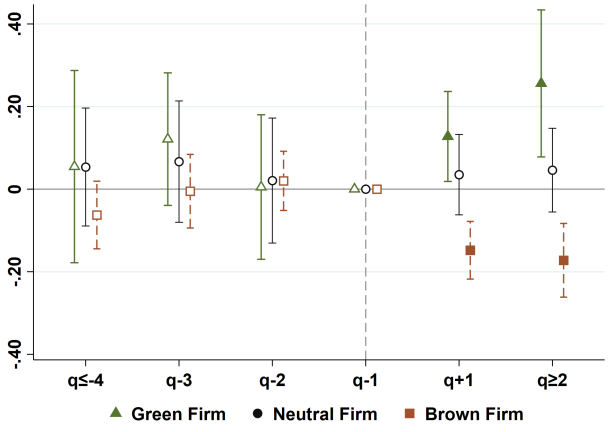
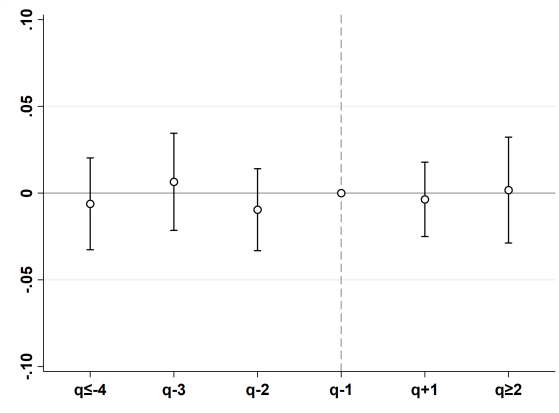
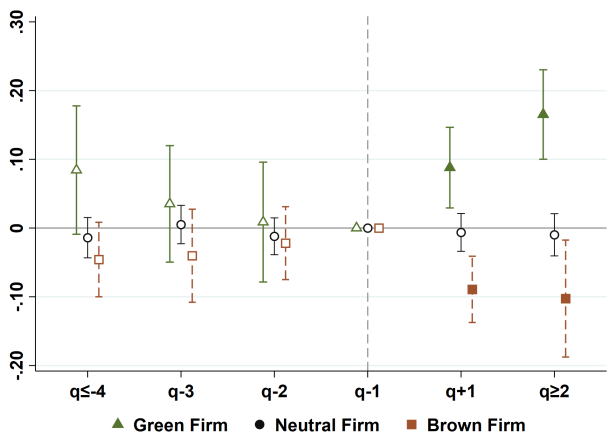


Figure 2 (Continued)

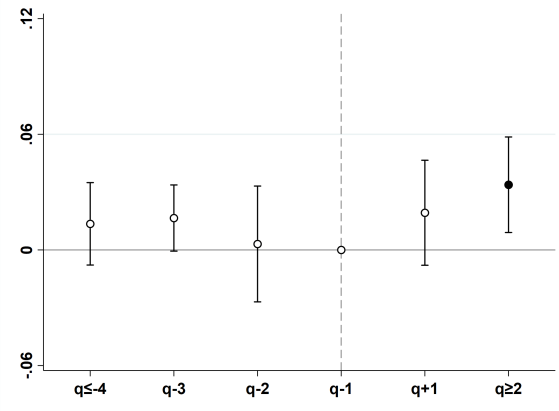
(m) *Report Tone* - Full sample



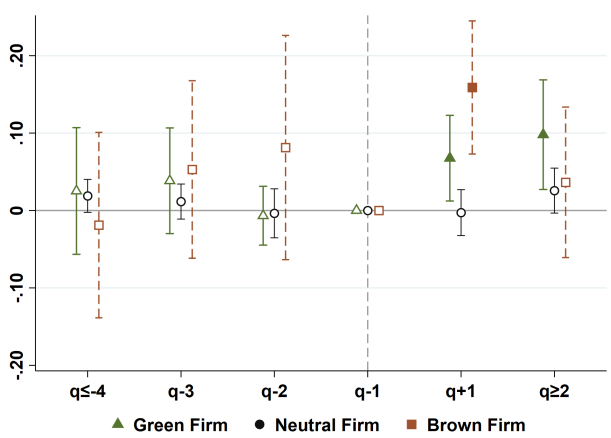
(n) *Report Tone* - Heterogeneity tests



(o) *Forecast Accuracy* - Full sample



(p) *Forecast Accuracy* - Heterogeneity tests



Notes: This figure presents event-study estimates of the effect of the monitoring program on several outcome variables. The panels are arranged in pairs, one pair per dependent variable: within each pair, the first (left) panel reports estimates for the full sample and the second (right) panel reports the heterogeneity tests. Panels (a) and (b) use *Air Pollution Discussed*, Panels (c) and (d) use *Market Reaction (%)*, Panels (e) and (f) use *Site Visit*, Panels (g) and (h) use *EPS Forecast (%)*, Panels (i) and (j) use *Recommendation*, Panels (k) and (l) use *Target Price*, Panels (m) and (n) use *Report Tone*, and Panels (o) and (p) use *Forecast Accuracy*. In the full-sample panels, 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 the quarter immediately before implementation *q-1*, which is the base quarter). The endpoint indicators $q \leq -4$ and $q \geq 2$ pool all quarters four or more quarters before and two or more quarters after implementation, respectively. In the heterogeneity panels, we partition analyst reports into three groups, *Brown*, *Neutral*, and *Green*, and estimate Equation 2 separately for each group. Specifically, we instruct *DeepSeek-Reasoner* to focus exclusively on the firm's business description in the MD&A section of the 2011 annual reports 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*. Green, brown, and neutral firms are plotted as green, brown, and black lines, respectively. Vertical lines represent the 90% confidence intervals for each parameter estimate, using standard errors clustered at the City × Year level. Significant coefficients are plotted as solid markers, and insignificant coefficients are plotted as hollow markers.

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. 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
Transition Risks Discussed	67,389	0.025	0.157	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
Stakeholder Risks Discussed	67,389	0.001	0.024	0.000	0.000	0.000
Current Regulatory Risks Discussed	67,389	0.013	0.114	0.000	0.000	0.000
Future Regulatory Risks Discussed	67,389	0.018	0.132	0.000	0.000	0.000
Current Preference-related Factors Discussed	67,389	0.012	0.110	0.000	0.000	0.000
Future Preference-related Factors Discussed	67,389	0.018	0.133	0.000	0.000	0.000
Market Reaction (%)	56,393	0.868	4.619	−1.959	0.367	3.164
Post-Analyst-Report BHAR (%)	56,393	−3.055	34.166	−25.492	−7.987	12.853
Market Reaction to Earnings Announcement (%)	11,591	3.292	3.047	1.097	2.440	4.513
Treated Analyst Ratio	11,591	0.000	1.000	−0.913	−0.913	1.181
Site Visit	63,747	0.038	0.192	0.000	0.000	0.000
Pollution Discussed During Site Visits	3,597	0.045	0.207	0.000	0.000	0.000
Treated Analyst Ratio (Site Visits)	3,597	0.000	1.000	0.244	0.244	0.244
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
Forecast Accuracy	67,061	−0.614	1.378	−0.556	−0.183	−0.068
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	67,389	0.109	0.312	0.000	0.000	0.000
Neutral Firm	67,389	0.785	0.411	1.000	1.000	1.000
Brown Firm	67,389	0.106	0.308	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*). *Market Reaction (%)* is the (signed) cumulative abnormal return over a three-day window centered on the analyst report date, multiplied by 100. *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. Negative and positive words are identified using the Loughran-McDonald dictionary. All continuous variables are winsorized at the 1% and 99% levels. All variables are defined in the Variable Appendix.

Table 3. Effect of the monitoring program on public access to and awareness of air quality information

$y \Rightarrow$	(1) *News Coverage*	(2) *Internet Search*
Treated City × *Post*	0.954***	0.318***
	(0.221)	(0.099)
Obs. (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 of 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 treated 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 4. Analyst discussions of air pollution and placebo topics

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)
Obs. (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)
Obs. (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 $\times$ 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

Panel A. Aggregate categories

$y \Rightarrow$	(1) *Physical Risks*	(2) *Transition Risks*
Treated × *Post*	0.000	0.018***
	(0.000)	(0.005)
Obs. (Analyst Report-Cohort Level)	67,389	67,389
Number of Unique Analysts	715	715
Number of Unique Firms	1,460	1,460
FEs included in Table 4	Yes	Yes
Adj. R^2	23.5%	45.9%
Pre-program Mean of y	0.001	0.021
Pre-program Standard Deviation of y	0.031	0.143

Panel B. Components of transition risks

$y \Rightarrow$	(1) *Regulatory Risks*	(2) *Preference Factors*	(3) *Stakeholder Risks*
Treated × *Post*	0.017***	0.013***	0.000
	(0.005)	(0.003)	(0.000)
Obs. (Analyst Report-Cohort Level)	67,389	67,389	67,389
Number of Unique Analysts	715	715	715
Number of Unique Firms	1,460	1,460	1,460
FEs included in Table 4	Yes	Yes	Yes
Adj. R^2	42.5%	46.3%	33.9%
Pre-program Mean of y	0.018	0.016	0.000
Pre-program Standard Deviation of y	0.133	0.124	0.020

Panel C. Current versus future regulatory risks and preference-related factors

$y \Rightarrow$	(1) *Current Regulatory Risks*	(2) *Future Regulatory Risks*	(3) *Current Preference Factors*	(4) *Future Preference Factors*
Treated × *Post*	0.008***	0.014***	0.003*	0.013***
	(0.003)	(0.004)	(0.002)	(0.002)
Obs. (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
FEs included in Table 4	Yes	Yes	Yes	Yes
Adj. R^2	41.1%	43.0%	51.0%	46.7%
Pre-program Mean of y	0.012	0.015	0.011	0.015
Pre-program Standard Deviation of y	0.108	0.123	0.103	0.122

Notes: This table reports the effects of the monitoring program on analyst discussions of different types of environmental risks. Panel A reports the two aggregate risk categories: *Physical Risks* equals one if the analyst discusses physical risks arising from climate change or air pollution, and *Transition Risks* equals one if the analyst discusses any transition risk, defined as the risk to a firm's cash flows arising from the economy's adjustment toward lower emissions. Panel B decomposes *Transition Risks* into its components: *Regulatory Risks* equals one if the analyst discusses environmental regulatory risks, *Preference Factors* equals one if the analyst discusses changes in customer preference and demand driven by pollution or climate concerns, and *Stakeholder Risks* equals one if the analyst discusses environmental risks related to stakeholders such as shareholders or supply-chain partners. Panel C splits the regulatory and preference categories into their current and future parts. *Current Regulatory Risks* equals one if the analyst discusses environmental risks related to regulatory exposure that is already in place or already happening (e.g., existing laws, carbon price or tax in force). *Future Regulatory Risks* equals one if the analyst discusses environmental risks related to regulatory exposure that is anticipated or expected but not yet binding (e.g., expected tightening of rules, proposed policies). *Current Preference Factors* equals one if the analyst discusses a demand shift that has already been observed or is affecting the firm. *Future Preference Factors* equals one if the analyst discusses a demand shift that is anticipated or expected to develop. *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 $\times$ Year level and reported in parentheses. *, **, *** indicate statistical significance at the 10%, 5%, and 1% levels (two-sided), respectively.

Table 6. Heterogeneity tests

$y \Rightarrow$	(1)	(2)	(3)
	Air Pollution Discussed		
	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	
Obs. (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

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. We partition analyst reports into three groups: *Brown*, *Neutral*, and *Green*. Specifically, 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. *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. Market reaction to analyst reports

$y \Rightarrow$	(1)	(2)	(3)	(4)
		Market Reaction (%)		
	Full Sample	*Heterogeneity Tests*		
		Green	*Neutral*	*Brown*
Treated × *Post*	−0.121	0.834**	−0.113	−1.185***
	(0.197)	(0.393)	(0.223)	(0.308)
p-value for $\beta_{Green} - \beta_{Neutral} > 0$			0.009	
p-value for $\beta_{Neutral} - \beta_{Brown} > 0$			0.002	
p-value for $\beta_{Green} - \beta_{Brown} > 0$			0.000	
Obs. (Analyst Report-Cohort Level)	56,393	6,276	44,227	5,890
Number of Unique Analysts	713	291	681	255
Number of Unique Firms	1,448	184	1,117	147
Firm × Year-Quarter × Cohort FE	Yes	Yes	Yes	Yes
Analyst × Firm × Cohort FE	Yes	Yes	Yes	Yes
Adj. R^2	32.3%	27.0%	33.3%	28.9%
Pre-program Mean of y	0.976	0.821	1.014	0.859
Pre-program Standard Deviation of y	4.723	4.721	4.745	4.555

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*. Specifically, 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. *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. To create the sample for this test, we exclude analyst reports issued on the same day as the firm's annual earnings announcement or mandatory earnings preannouncement, to avoid capturing market reactions driven by those disclosures rather than analyst reports. 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. Stock return reversal

$y \Rightarrow$	(1)	(2)	(3)	(4)
	Post-Analyst-Report BHAR (%)			
	Full Sample	*Heterogeneity Tests*		
		Green	*Neutral*	*Brown*
Treated × *Post* × *Market Reaction (%)*	0.068	−0.409	0.129	0.177
	(0.099)	(0.402)	(0.087)	(0.217)
Treated × *Post*	−0.008	−1.297	0.036	1.154
	(0.346)	(0.987)	(0.357)	(0.807)
Treated × *Market Reaction (%)*	−0.012	0.197	−0.032	−0.090
	(0.043)	(0.141)	(0.045)	(0.132)
Post × *Market Reaction (%)*	−0.141*	0.436	−0.237***	−0.019
	(0.080)	(0.272)	(0.066)	(0.169)
Market Reaction (%)	−0.286***	−0.613***	−0.258***	−0.142
	(0.052)	(0.168)	(0.049)	(0.161)
Obs. (Analyst Report-Cohort Level)	56,393	6,276	44,227	5,890
Number of Unique Analysts	713	291	681	255
Number of Unique Firms	1,448	184	1,117	147
Firm × Year-Quarter × Cohort FE	Yes	Yes	Yes	Yes
Analyst × Firm × Cohort FE	Yes	Yes	Yes	Yes
Adj. R^2	94.2%	94.5%	94.1%	94.4%
Pre-program Mean of y	−0.791	−1.666	−0.090	−4.951
Pre-program Standard Deviation of y	27.789	27.163	28.389	23.309

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 BHARs 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 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 separate regressions for analyst reports covering firms in each of these three groups. *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. Stock price efficiency

	(1)	(2)	(3)	(4)
$y \Rightarrow$	*Market Reaction to Earnings Announcement (%)*			
	Full Sample	*Heterogeneity Tests*		
		Green	*Neutral*	*Brown*
Treated Analyst Ratio	−0.020	−0.534**	0.114	−0.516**
	(0.085)	(0.228)	(0.097)	(0.255)
p-value for $\beta_{Green} - \beta_{Neutral} < 0$			0.005	
p-value for $\beta_{Brown} - \beta_{Neutral} < 0$			0.010	
p-value for $\beta_{Green} - \beta_{Brown} < 0$			0.479	
Obs. (Firm-Year-Quarter Level)	11,591	1,409	8,914	1,268
Number of Unique Firms	1,459	184	1,126	149
Firm FE	Yes	Yes	Yes	Yes
Year-Quarter FE	Yes	Yes	Yes	Yes
Adj. R^2	7.9%	6.9%	8.1%	8.5%
Mean of y	3.292	3.316	3.326	3.028
Standard Deviation of y	3.047	2.962	3.079	2.901

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 number 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 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 separate regressions for firms in each of these three groups. 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.

Table 10. Site visits

Panel A. Probability of site visits

	(1)	(2)	(3)	(4)
$y \Rightarrow$		*Site Visit*		
	Full Sample	*Heterogeneity Tests*		
		Green	*Neutral*	*Brown*
Treated × *Post*	0.021***	0.046***	0.012	0.076**
	(0.006)	(0.016)	(0.008)	(0.036)
p-value for $\beta_{Green} - \beta_{Neutral} > 0$			0.045	
p-value for $\beta_{Brown} - \beta_{Neutral} > 0$			0.059	
p-value for $\beta_{Green} - \beta_{Brown} > 0$			0.868	
Obs. (Firm-Analyst-Year-Quarter-Cohort)	63,747	7,643	50,938	5,166
Number of Unique Analysts	657	234	608	180
Number of Unique Firms	929	125	726	78
Firm × Year-Quarter × Cohort FE	Yes	Yes	Yes	Yes
Analyst × Firm × Cohort FE	Yes	Yes	Yes	Yes
Adj. R^2	38.3%	31.2%	41.4%	20.1%
Pre-program Mean of y	0.017	0.015	0.014	0.051
Pre-program Standard Deviation of y	0.130	0.122	0.117	0.219

Panel B. Air pollution discussion during site visits

	(1)	(2)	(3)	(4)
$y \Rightarrow$		*Pollution Discussed During Site Visits*		
	Full Sample	*Heterogeneity Tests*		
		Green	*Neutral*	*Brown*
Treated Analyst Ratio (Site Visits)	0.007**	0.027**	0.001	0.024**
	(0.003)	(0.013)	(0.002)	(0.010)
p-value for $\beta_{Green} - \beta_{Neutral} > 0$			0.027	
p-value for $\beta_{Brown} - \beta_{Neutral} > 0$			0.015	
p-value for $\beta_{Green} - \beta_{Brown} > 0$			0.439	
Obs. (Firm-Visit)	3,597	450	2,857	290
Number of Unique Firms	718	105	560	53
Firm FE	Yes	Yes	Yes	Yes
Year-Quarter FE	Yes	Yes	Yes	Yes
Adj. R^2	48.9%	60.2%	38.4%	3.5%
Mean of y	0.045	0.184	0.025	0.031
Standard Deviation of y	0.207	0.388	0.155	0.174

Table 10 (Continued)

Notes: Panel A reports the effect of the monitoring program on the probability that an analyst conducts a corporate site visit. Panel B reports results on the effect of the monitoring program on discussions during analysts' corporate site visits. In Panel A, the sample is at the firm-analyst-year-quarter-cohort level and covers 2010Q1–2013Q3. *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. *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. In Panel B, the sample is at the firm-visit level and covers 2012Q1–2013Q3. The sample begins in 2012, rather than 2010, because data on the content of discussions during site visits are limited before 2012. *Pollution Discussed During Site Visits* is an indicator variable that equals one if air quality is discussed during the question-and-answer portion of the site visit, and zero otherwise. *Treated Analyst Ratio (Site Visits)* is the fraction of analysts attending the visit who are based in cities that had already implemented the monitoring program as of the visit date. We standardize this measure to have a mean of zero and a standard deviation of one. In both panels, Column 1 reports evidence for the full sample. 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 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 separate regressions for each of these three groups. All variables are defined in the Variable Appendix. Standard errors are clustered at the City × Year level in Panel A and at the firm level in Panel B, and are reported in parentheses. *, **, *** indicate statistical significance at the 10%, 5%, and 1% levels (two-sided), respectively.

Table 11. Analyst outputs

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)
Obs. (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

Panel B. Heterogeneity tests

$y \Rightarrow$	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	EPS Forecast (%)			*Recommendation*			*Target Price*			*Report Tone*		
	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 11 (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. *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. Negative and positive words are identified using the Loughran-McDonald dictionary. 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. *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 12. Forecast accuracy

$y \Rightarrow$	(1)	(2)	(3)	(4)
	Forecast Accuracy			
	Full Sample	*Heterogeneity Tests*		
		Green	*Neutral*	*Brown*
Treated × *Post*	0.016**	0.068***	−0.001	0.100***
	(0.007)	(0.025)	(0.007)	(0.021)
p-value for $\beta_{Green} - \beta_{Neutral} > 0$			0.001	
p-value for $\beta_{Brown} - \beta_{Neutral} > 0$			0.000	
p-value for $\beta_{Green} - \beta_{Brown} > 0$			0.816	
Obs. (Analyst Report-Cohort Level)	67,061	7,321	52,645	7,095
Number of Unique Analysts	715	292	684	257
Number of Unique Firms	1,460	184	1,127	149
Firm × Year-Quarter × Cohort FE	Yes	Yes	Yes	Yes
Analyst × Firm × Cohort FE	Yes	Yes	Yes	Yes
Adj. R^2	96.3%	97.6%	96.4%	94.8%
Pre-program Mean of y	−0.557	−0.585	−0.530	−0.726
Pre-program Standard Deviation of y	1.276	1.254	1.249	1.465

Notes: This table reports the effect of the monitoring program on analyst forecast accuracy. *Forecast Accuracy* of a report issued by analyst j for firm i equals negative one multiplied by $|$*Analyst EPS Forecast*$-$*Actual EPS*$|$ divided by $|$*Actual EPS*$|$, where *Analyst EPS Forecast* is analyst j's EPS forecast issued for firm i and *Actual EPS* is firm i's actual EPS. Column 1 reports evidence on the effects of the monitoring program on forecast accuracy using a stacked cohort DiD design. In Columns 2–4, we partition analyst reports into three groups: *Brown*, *Neutral*, and *Green*. Specifically, 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. *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.

Internet Appendix

Pollution Monitoring and the Pricing of Environmental Risk in Firms

Internet Appendix Contents

Internet Appendix A Additional Analyses 1

A.1 Alternative heterogeneity tests: Government-designated classification 1

A.2 Alternative research design: Cross-listed firms 2

Figure A1. Stacked cohort DiD design: Treated analyst reports vs. not-yet-treated 4

Table A1. Variable Definitions 6

Table A2. Sample selection 9

Table A3. Alternative heterogeneity tests: Government-designated Classification 10

Table A4. Heterogeneity tests for different types of environmental risks 11

Table A5. Stock return reversal over one month following the analyst report date 12

Table A6. Profitability of stock recommendation 13

Table A7. Cross-listed sample tests 14

Table A8. Additional heterogeneity tests 18

Table A9. Alternative proxy for air pollution discussion 19

Table A10. Alternative specification for heterogeneity tests: Triple interaction 20

Table A11. Subsample limited to analysts in cities different from the covered firm's city 21

Table A12. Subsample limited to analyst reports issued for never-treated firms 23

Table A13. Clustering standard errors at the city level 25

Table A14. Including control variables 27

Table A15. Distance between the analyst's city and the covered firm's city 30

Internet Appendix B Large Language Model 31

B.1 Model performance 31

B.2 Choice of language model 32

Figure B1. Time trend in *Air Pollution Discussed* measure 33

Table B1. *DeepSeek* classification performance 34

Internet Appendix C Examples of air pollution discussions in analyst reports 35

Internet Appendix A Additional Analyses

A.1 Alternative heterogeneity tests: Government-designated classification

In Section 5.2.3, we measure a firm's exposure to environmental risk using an LLM-based classification that sorts firms into brown, green, and neutral groups. In this section, we assess whether those findings are robust to an alternative, government-designated measure of firms negatively exposed to environmental risks.

To measure firms' exposure to environmental risks, we use the Environmental Survey and Reporting (ESR) database, a proprietary firm-level dataset administered by China's Ministry of Environmental Protection (MEP).[1] 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 near-complete coverage of major emitters and serves as the primary data source for studying environmental regulation in China.[2] 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. We then re-estimate Equation 2 separately for analyst reports covering *Brown* and *Not Brown* firms, using the same outcome variables examined in the main analyses: *Air Pollution Discussed*, *EPS Forecast*, *Recommendation*, *Target Price*, *Report Tone*, and *Market Reaction*.

Table A3 reports the results. Consistent with our LLM-based findings, the effects of the monitoring program are concentrated among brown firms. Columns 1 and 2 show that treated analysts' discussion of air pollution increases by 8.4 percentage points for *Brown* firms following the program, relative to control analysts covering the same firms, compared with 1.1 percentage points for *Not Brown* firms, and the difference is statistically significant.

Columns 3 and 4 show that, following the program, reports issued by treated analysts generate market reactions that are 1.31 percentage points more negative for *Brown* firms, relative to control analysts covering the same firms, whereas the corresponding difference for *Not Brown* firms is 0.06 percentage points and statistically indistinguishable from zero.

Finally, Columns 5 through 12 show that, 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

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

[2] 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.

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*. In contrast, we find no significant differences between treated and control analyst reports for *Not Brown* firms, and the differences between the two groups are statistically significant across all measures.

Overall, the government-designated classification yields the same pattern as our LLM-based measure: the program's effects on analysts' air pollution discussions and outputs and the market's response are concentrated among the highest-emitting firms, for which environmental risks are most likely to be financially material.

A.2 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 the *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:

$$y_{i,j,q} = \beta \, \textit{Mainland China}_i \times \textit{Alternative Post}_q + \alpha_{j,q} + \alpha_{i,j} + \varepsilon_{i,j,q} \tag{IA1}$$

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 Forecast*, *Recommendation*, *Target Price*, *Report Tone*, and *Market Reaction*. $\textit{Mainland China}_i$ is an indicator variable that equals one for analysts residing in mainland China and zero for analysts residing outside mainland China. $\textit{Alternative Post}_q$ 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.[3] 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 A7 presents the results from estimating Equation IA1 using analysts covering Chinese cross-listed firms. Overall, the results are generally consistent with our main identification strategy.

References

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

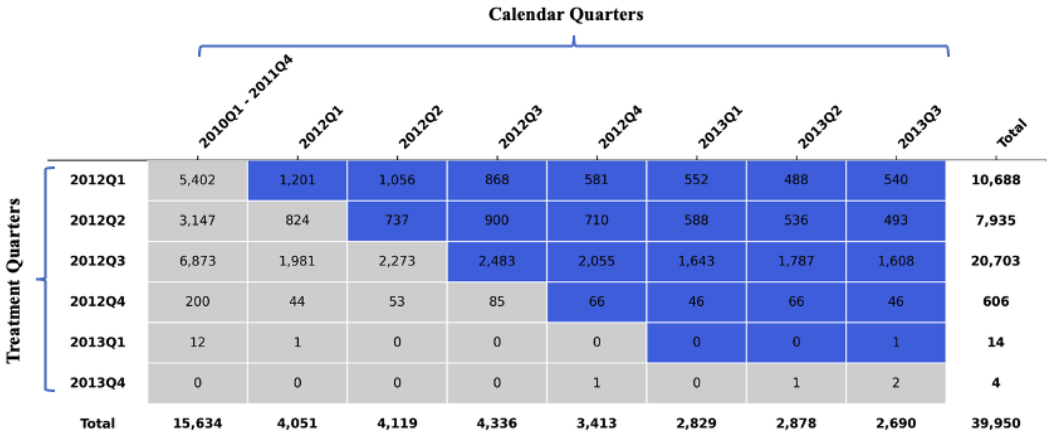
He, G., Wang, S., and Zhang, B. (2020). Watering down environmental regulation in China. *The Quarterly Journal of Economics*, 135(4):2135–2185.

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.

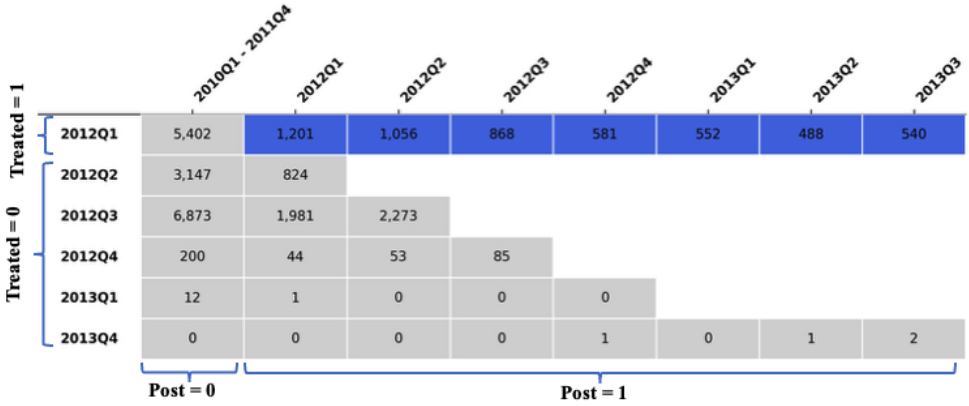
[3] Our fixed effects subsume the main effects of *Mainland China* and *Alternative Post*.

Figure A1. Stacked cohort DiD design: Treated analyst reports vs. not-yet-treated analyst reports

(a) Distribution of analyst reports across quarters in the final sample



(b) Cohort 1 (2012Q1 vs. 2012Q2–2013Q4)



(c) Cohort 2 (2012Q2 vs. 2012Q3–2013Q4)

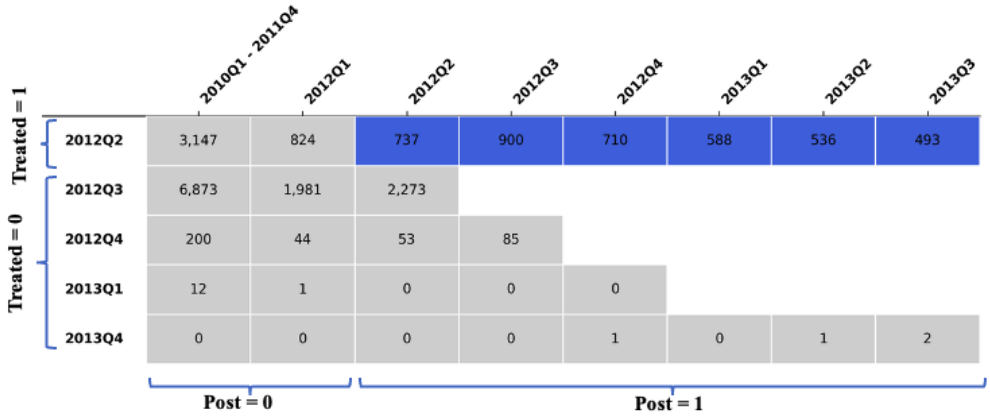


Figure A1 (Continued)

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 treated (post-adoption) calendar quarters, 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.

Table A1. Variable Definitions

Variable	Definition	Data Source
Stock return reversal over one month following the analyst report date [Table A5]		
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-month period after the analyst report date.	CSMAR
Profitability of stock recommendation [Table A6]		
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, 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.	CNRDS & CSMAR
Cross-listed tests [Table A7]		
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.	
Alternative heterogeneity tests: Government-designated classification [Table A3]		

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 classified as *Brown Firm–Govt*.	ESR
Additional heterogeneity variables [Table A8]		
City with the U.S. Embassy	An indicator variable that equals one for all observations in cohort 1, in which Beijing, the city that hosts the U.S. Embassy, is the treated city, and zero for observations in cohorts 2 to 5.	
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 New Fortune in 2011.	CNRDS
Alternative proxy for air pollution discussions in analyst reports [Table A9]		
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 A12]		
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 A14]		
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
Distance between the analyst's city and the covered firm's city [Table A15]		
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.	China Economic Research Series of CSMAR

Table A2. Sample selection

Description	Number of Reports	Number of Firms	Number of Analysts
Reports from CnOpenData issued from 2010Q1 through 2015Q4	217,510	2,777	3,218
Remove:			
Reports not matched to the CNRDS analyst database	(30,599)	(58)	(203)
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)
Reports 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 A3. Alternative heterogeneity tests: Government-Designated Classification

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
$y \Rightarrow$	*Air Pollution Discussed*		*Market Reaction (%)*		*EPS Forecast (%)*		*Recommendation*		*Target Price*		*Report Tone*	
Govt-designated classification $\Rightarrow$	*Not Brown*	*Brown*	*Not Brown*	*Brown*	*Not Brown*	*Brown*	*Not Brown*	*Brown*	*Not Brown*	*Brown*	*Not Brown*	*Brown*
Treated × *Post*	0.011***	0.084***	0.062	−1.312***	0.040	−0.125***	0.021	−0.125***	0.027	−0.147**	0.009	−0.043**
	(0.003)	(0.031)	(0.200)	(0.431)	(0.025)	(0.044)	(0.016)	(0.038)	(0.041)	(0.065)	(0.009)	(0.017)
p-value for $\beta_{Brown} - \beta_{Not\ Brown} > 0$		0.008										
p-value for $\beta_{Not\ Brown} - \beta_{Brown} > 0$			0.000		0.002		0.000		0.030		0.000	
Obs. (Analyst Report-Cohort Level)	55,182	12,207	46,173	10,220	54,949	12,122	53,663	11,726	17,958	3,747	55,182	12,207
Number of Unique Analysts	690	462	689	460	690	462	687	459	534	302	690	462
Number of Unique Firms	1,107	353	1,100	348	1,105	353	1,093	350	855	258	1,107	353
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	44.8%	50.9%	32.4%	30.9%	96.8%	95.6%	79.1%	76.3%	76.6%	78.6%	47.5%	46.1%
Pre-program Mean of y	0.022	0.020	0.952	1.081	4.673	4.341	4.336	4.311	1.248	1.208	−0.031	−0.061
Pre-program Standard Deviation of y	0.146	0.139	4.695	4.841	3.171	2.609	0.600	0.598	0.609	0.565	0.292	0.283

Notes: This table reports results on whether the effect of the monitoring program varies with the firms' pollution levels. 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). All variables are defined in the Variable Appendix in the paper or in Table A1. 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 A4. Heterogeneity tests for different types of environmental risks

Panel A. Heterogeneity tests for regulatory risks discussed

	(1)	(2)	(3)
$y \Rightarrow$	*Regulatory Risks Discussed*		
	Heterogeneity Tests		
	Green	*Neutral*	*Brown*
Treated × *Post*	0.090***	0.003	0.057***
	(0.022)	(0.003)	(0.016)
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	
Obs. (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	38.3%	41.1%	34.7%
Pre-program Mean of y	0.068	0.010	0.024
Pre-program Standard Deviation of y	0.252	0.100	0.154

Panel B. Heterogeneity tests for preference-related factors discussed

	(1)	(2)	(3)
$y \Rightarrow$	*Preference-related Factors Discussed*		
	Heterogeneity Tests		
	Green	*Neutral*	*Brown*
Treated × *Post*	0.054**	0.005***	0.033**
	(0.020)	(0.002)	(0.013)
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	
Obs. (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%	45.8%	6.9%
Pre-program Mean of y	0.071	0.008	0.012
Pre-program Standard Deviation of y	0.258	0.092	0.108

Notes: This table reports results on the heterogeneity of the effect of the monitoring program on analyst discussions of different types of environmental risks. 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 A5. Stock return reversal over one month following the analyst report date

$y \Rightarrow$	(1)	(2)	(3)	(4)
	Post-Analyst-Report 1-Month BHAR (%)			
	Full Sample	*Heterogeneity Tests*		
		Green	*Neutral*	*Brown*
Treated × *Post* × *Market Reaction (%)*	−0.033	−0.279	−0.027	0.135
	(0.079)	(0.323)	(0.070)	(0.227)
Treated × *Post*	−0.338	−1.348	−0.263	−0.001
	(0.281)	(0.846)	(0.266)	(0.663)
Treated × *Market Reaction (%)*	0.015	0.079	0.028	−0.146
	(0.027)	(0.136)	(0.033)	(0.103)
Post × *Market Reaction (%)*	−0.042	0.426	−0.072	−0.316
	(0.066)	(0.354)	(0.075)	(0.243)
Market Reaction (%)	−0.152***	−0.408	−0.129*	−0.054
	(0.056)	(0.250)	(0.073)	(0.114)
Obs. (Analyst Report-Cohort Level)	56,249	6,269	44,096	5,884
Number of Unique Analysts	713	291	681	255
Number of Unique Firms	1,448	184	1,117	147
Firm × Year-Quarter × Cohort FE	Yes	Yes	Yes	Yes
Analyst × Firm × Cohort FE	Yes	Yes	Yes	Yes
Adj. R^2	42.8%	35.1%	43.5%	44.7%
Pre-program Mean of y	−0.494	−0.293	−0.385	−1.480
Pre-program Standard Deviation of y	8.421	8.546	8.382	8.511

Notes: This table examines the return reversal of market reaction to analyst reports. All variables are defined in the Variable Appendix in the paper or in Table A1. 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 A6. Profitability of stock recommendation

	(1)	(2)	(3)	(4)
$y \Rightarrow$	*Profitability of Stock Recommendation (%)*			
	Full Sample	*Heterogeneity Tests*		
		Green	*Neutral*	*Brown*
Treated × *Post*	0.267*	1.361***	0.009	1.178*
	(0.145)	(0.355)	(0.198)	(0.653)
p-value for $\beta_{Green} - \beta_{Neutral} > 0$			0.003	
p-value for $\beta_{Brown} - \beta_{Neutral} > 0$			0.055	
p-value for $\beta_{Green} - \beta_{Brown} > 0$			0.384	
Obs. (Analyst Report-Cohort Level)	54,448	6,037	42,614	5,797
Number of Unique Analysts	709	289	677	255
Number of Unique Firms	1,428	183	1,099	146
Firm × Year-Quarter × Cohort FE	Yes	Yes	Yes	Yes
Analyst × Firm × Cohort FE	Yes	Yes	Yes	Yes
Adj. R^2	19.2%	13.5%	20.1%	18.1%
Pre-program Mean of y	0.756	0.690	0.773	0.697
Pre-program Standard Deviation of y	4.299	4.378	4.270	4.423

Notes: This table examines the effect of the monitoring program on the profitability of analysts' stock recommendations. All variables are defined in the Variable Appendix in the paper or in Table A1. 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 A7. Cross-listed sample tests

Panel A. *Air Pollution Discussed*

	(1)	(2)	(3)	(4)
$y \Rightarrow$		*Air Pollution Discussed*		
	Full Sample	*Heterogeneity Tests*		
		Green	*Neutral*	*Brown*
Mainland China × *Alternative Post*	0.028**	0.181***	−0.002	0.070***
	(0.014)	(0.042)	(0.014)	(0.019)
p-value for $\beta_{Green} - \beta_{Neutral} > 0$			0.000	
p-value for $\beta_{Brown} - \beta_{Neutral} > 0$			0.003	
p-value for $\beta_{Green} - \beta_{Brown} > 0$			0.008	
Obs. (Analyst Report Level)	16,781	1,728	13,126	1,927
Number of Unique Analysts	1,619	435	1,382	351
Number of Unique Firms	72	7	57	8
Firm × Year-Quarter FE	Yes	Yes	Yes	Yes
Analyst × Firm FE	Yes	Yes	Yes	Yes
Adj. R^2	24.1%	34.2%	19.2%	12.5%
Pre-program Mean of y	0.016	0.068	0.007	0.027
Pre-program Standard Deviation of y	0.125	0.252	0.080	0.161

Panel B. *Market Reaction (%)*

	(1)	(2)	(3)	(4)
$y \Rightarrow$		*Market Reaction (%)*		
	Full Sample	*Heterogeneity Tests*		
		Green	*Neutral*	*Brown*
Mainland China × *Alternative Post*	0.397	−0.683	0.835	−1.448**
	(0.546)	(1.054)	(0.639)	(0.601)
p-value for $\beta_{Green} - \beta_{Neutral} > 0$			0.900	
p-value for $\beta_{Neutral} - \beta_{Brown} > 0$			0.005	
p-value for $\beta_{Green} - \beta_{Brown} > 0$			0.260	
Obs. (Analyst Report Level)	14,337	1,542	11,164	1,631
Number of Unique Analysts	1,575	420	1,332	337
Number of Unique Firms	66	7	51	8
Firm × Year-Quarter FE	Yes	Yes	Yes	Yes
Analyst × Firm FE	Yes	Yes	Yes	Yes
Adj. R^2	36.5%	41.1%	34.0%	44.9%
Pre-program Mean of y	0.405	1.084	0.336	0.131
Pre-program Standard Deviation of y	4.525	5.193	4.390	4.612

Table A7 (Continued)

Panel C. *EPS Forecast (%)*

$y \Rightarrow$	(1)	(2)	(3)	(4)
	EPS Forecast (%)			
	Full Sample	*Heterogeneity Tests*		
		Green	*Neutral*	*Brown*
Mainland China × *Alternative Post*	−0.070	0.609**	0.006	−0.619**
	(0.183)	(0.167)	(0.237)	(0.245)
p-value for $\beta_{Green} - \beta_{Neutral} > 0$			0.013	
p-value for $\beta_{Neutral} - \beta_{Brown} > 0$			0.033	
p-value for $\beta_{Green} - \beta_{Brown} > 0$			0.001	
Obs. (Analyst Report Level)	15,538	1,675	12,044	1,819
Number of Unique Analysts	1,589	434	1,342	348
Number of Unique Firms	65	7	50	8
Firm × Year-Quarter FE	Yes	Yes	Yes	Yes
Analyst × Firm FE	Yes	Yes	Yes	Yes
Adj. R^2	93.8%	94.8%	94.9%	80.7%
Pre-program Mean of y	5.797	4.579	6.144	4.715
Pre-program Standard Deviation of y	3.734	2.741	3.875	3.144

Panel D. *Recommendation*

$y \Rightarrow$	(1)	(2)	(3)	(4)
	Recommendation			
	Full Sample	*Heterogeneity Tests*		
		Green	*Neutral*	*Brown*
Mainland China × *Alternative Post*	−0.029	0.236	0.019	−0.325*
	(0.075)	(0.143)	(0.081)	(0.140)
p-value for $\beta_{Green} - \beta_{Neutral} > 0$			0.080	
p-value for $\beta_{Neutral} - \beta_{Brown} > 0$			0.014	
p-value for $\beta_{Green} - \beta_{Brown} > 0$			0.004	
Obs. (Analyst Report Level)	16,487	1,709	12,932	1,846
Number of Unique Analysts	1,597	426	1,364	338
Number of Unique Firms	72	7	57	8
Firm × Year-Quarter FE	Yes	Yes	Yes	Yes
Analyst × Firm FE	Yes	Yes	Yes	Yes
Adj. R^2	73.8%	72.3%	74.2%	68.5%
Pre-program Mean of y	3.962	4.135	3.966	3.744
Pre-program Standard Deviation of y	0.738	0.717	0.727	0.780

Table A7 (Continued)

Panel E. *Target Price*

$y \Rightarrow$	(1)	(2)	(3)	(4)
	Target Price			
	Full Sample	*Heterogeneity Tests*		
		Green	*Neutral*	*Brown*
Mainland China × *Alternative Post*	−0.017	0.158*	0.015	−0.222**
	(0.055)	(0.069)	(0.065)	(0.083)
p-value for $\beta_{Green} - \beta_{Neutral} > 0$			0.062	
p-value for $\beta_{Neutral} - \beta_{Brown} > 0$			0.009	
p-value for $\beta_{Green} - \beta_{Brown} > 0$			0.001	
Obs. (Analyst Report Level)	8,664	929	6,527	1,208
Number of Unique Analysts	1,086	260	897	232
Number of Unique Firms	65	7	50	8
Firm × Year-Quarter FE	Yes	Yes	Yes	Yes
Analyst × Firm FE	Yes	Yes	Yes	Yes
Adj. R^2	80.0%	84.3%	80.4%	74.2%
Pre-program Mean of y	1.115	1.038	1.159	0.931
Pre-program Standard Deviation of y	0.489	0.505	0.474	0.510

Panel F. *Report Tone*

$y \Rightarrow$	(1)	(2)	(3)	(4)
	Report Tone			
	Full Sample	*Heterogeneity Tests*		
		Green	*Neutral*	*Brown*
Mainland China × *Alternative Post*	0.032	0.126*	0.058	−0.101**
	(0.043)	(0.060)	(0.054)	(0.039)
p-value for $\beta_{Green} - \beta_{Neutral} > 0$			0.194	
p-value for $\beta_{Neutral} - \beta_{Brown} > 0$			0.007	
p-value for $\beta_{Green} - \beta_{Brown} > 0$			0.003	
Obs. (Analyst Report Level)	16,781	1,728	13,126	1,927
Number of Unique Analysts	1,619	435	1,382	351
Number of Unique Firms	72	7	57	8
Firm × Year-Quarter FE	Yes	Yes	Yes	Yes
Analyst × Firm FE	Yes	Yes	Yes	Yes
Adj. R^2	46.7%	45.0%	46.1%	49.6%
Pre-program Mean of y	−0.082	−0.070	−0.075	−0.145
Pre-program Standard Deviation of y	0.304	0.299	0.304	0.301

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), *Market Reaction (%)* (Panel B), *EPS Forecast (%)* (Panel C), *Recommendation* (Panel D), *Target Price* (Panel E), and *Report Tone* (Panel F). All variables are defined in the Variable Appendix in the paper or in Table A1. 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 A8. Additional heterogeneity tests

	(1)	(2)	(3)	(4)	(5)	(6)
$y \Rightarrow$	*Air Pollution Discussed*					
Heterogeneity tests $\Rightarrow$	*City with the U.S. Embassy*		*Below-Median Analyst Age*		*Star Analyst*	
	No	*Yes*	*No*	*Yes*	*No*	*Yes*
Treated × *Post*	0.033***	0.017***	−0.002	0.044**	0.020***	0.088***
	(0.009)	(0.003)	(0.007)	(0.017)	(0.006)	(0.029)
p-value for $\beta_{No} - \beta_{Yes} > 0$	0.041					
p-value for $\beta_{Yes} - \beta_{No} > 0$			0.011		0.012	
Obs. (Analyst Report-Cohort Level)	41,204	26,185	21,619	21,569	50,266	17,123
Number of Unique Analysts	494	715	205	220	632	83
Number of Unique Firms	1,246	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	50.2%	41.7%	50.5%	52.4%	46.9%	46.6%
Pre-program Mean of y	0.022	0.020	0.025	0.020	0.022	0.021
Pre-program Standard Deviation of y	0.147	0.141	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-polluting activities in their reports varies with three variables: *City with the U.S. Embassy*, *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 Beijing, which hosts the U.S. Embassy, and estimate Equation 2 separately for these two groups of reports. Beijing belongs to cohort 1. Column 2 includes reports issued by analysts in Beijing and all control analyst reports in cohort 1. Column 1 includes all observations in cohorts 2, 3, 4, and 5. 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 Best Analyst Award from New Fortune in 2011, and estimate Equation 2 separately for these groups. All variables are defined in the Variable Appendix in the paper or in Table A1. 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 A9. Alternative proxy for air pollution discussion

	(1)	(2)	(3)	(4)
$y \Rightarrow$	*Air Pollution Discussed–Dict*			
	Full Sample	*Heterogeneity Tests*		
		Green	*Neutral*	*Brown*
Treated × *Post*	0.030***	0.064*	0.019*	0.075***
	(0.011)	(0.032)	(0.010)	(0.026)
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	
Obs. (Analyst Report-Cohort Level)	67,389	7,353	52,876	7,160
Number of Unique Analysts	715	292	684	257
Number of Unique Firms	1,460	184	1,127	149
Firm × Year-Quarter × Cohort FE	Yes	Yes	Yes	Yes
Analyst × Firm × Cohort FE	Yes	Yes	Yes	Yes
Adj. R^2	39.5%	46.9%	34.4%	15.4%
Pre-program Mean of y	0.023	0.080	0.014	0.029
Pre-program Standard Deviation of y	0.148	0.272	0.116	0.168

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: *Air Pollution Discussed–Dict* based on the dictionary of 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*, and estimate separate regressions for each of these three groups. All variables are defined in the Variable Appendix in the paper or in Table A1. 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 A10. Alternative specification for heterogeneity tests: Triple interaction

$y \Rightarrow$	(1) *Air Pollution Discussed*	(2) *Market Reaction (%)*	(3) *EPS Forecast (%)*	(4) *Recommendation*	(5) *Target Price*	(6) *Report Tone*
Treated×*Post*	0.013***	−0.113	0.042	0.002	0.007	−0.001
	(0.002)	(0.225)	(0.032)	(0.018)	(0.036)	(0.012)
Treated×*Post*×*Green Firm*	0.048**	0.947**	0.243**	0.150***	0.130**	0.082***
	(0.020)	(0.386)	(0.101)	(0.047)	(0.054)	(0.027)
Treated×*Post*×*Brown Firm*	0.037**	−1.072***	−0.482***	−0.167***	−0.136**	−0.062***
	(0.017)	(0.361)	(0.131)	(0.038)	(0.053)	(0.020)
Obs. (Analyst Report-Cohort Level)	67,389	56,393	67,071	65,389	21,705	67,389
Number of Unique Analysts	715	713	715	711	563	715
Number of Unique Firms	1,460	1,448	1,458	1,443	1,113	1,460
Firm × Year-Quarter × Cohort FE	Yes	Yes	Yes	Yes	Yes	Yes
Analyst × Firm × Cohort FE	Yes	Yes	Yes	Yes	Yes	Yes
Adj. R^2	47.4%	32.3%	96.7%	78.7%	76.9%	47.3%
Pre-program Mean of y	0.021	0.976	4.612	4.331	1.241	−0.037
Pre-program Standard Deviation of y	0.145	4.723	3.077	0.599	0.602	0.290

Notes: This table reports the results on the heterogeneity of the effect of the monitoring program on several analyst outcomes using an alternative specification. We estimate an augmented Equation 2 by adding the interaction term among *Green Firm*, *Treated*, and *Post* as well as the interaction term among *Brown Firm*, *Treated*, and *Post*. All variables are defined in the Variable Appendix in the paper or in Table A1. 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 A11. Subsample limited to analysts in cities different from the covered firm's city

	(1)	(2)	(3)	(4)
	Full Sample		*Heterogeneity Tests*	
		Green	*Neutral*	*Brown*
$y \Rightarrow$		*Air Pollution Discussed*		
Treated × *Post*	0.024***	0.068**	0.014***	0.055**
	(0.006)	(0.029)	(0.002)	(0.021)
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	
Obs. (Analyst Report-Cohort Level)	59,992	6,761	46,925	6,306
Number of Unique Analysts	698	273	662	239
Number of Unique Firms	1,387	174	1,069	144
$y \Rightarrow$		*Market Reaction (%)*		
Treated × *Post*	−0.188	0.819*	−0.171	−1.401***
	(0.187)	(0.428)	(0.196)	(0.420)
p-value for $\beta_{Green} - \beta_{Neutral} > 0$			0.008	
p-value for $\beta_{Neutral} - \beta_{Brown} > 0$			0.004	
p-value for $\beta_{Green} - \beta_{Brown} > 0$			0.000	
Obs. (Analyst Report-Cohort Level)	50,201	5,776	39,263	5,162
Number of Unique Analysts	696	272	660	237
Number of Unique Firms	1,377	174	1,061	142
$y \Rightarrow$		*EPS Forecast (%)*		
Treated × *Post*	0.030	0.276**	0.032	−0.232***
	(0.025)	(0.126)	(0.034)	(0.079)
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	
Obs. (Analyst Report-Cohort Level)	59,703	6,723	46,713	6,267
Number of Unique Analysts	698	272	662	239
Number of Unique Firms	1,385	173	1,069	143

Table A11 (Continued)

	(1)	(2)	(3)	(4)
	Full Sample	*Heterogeneity Tests*		
		Green	*Neutral*	*Brown*
$y \Rightarrow$		*Recommendation*		
Treated × *Post*	0.013	0.181**	0.020	−0.194***
	(0.021)	(0.071)	(0.021)	(0.036)
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	
Obs. (Analyst Report-Cohort Level)	58,150	6,537	45,398	6,215
Number of Unique Analysts	696	272	660	239
Number of Unique Firms	1,369	173	1,054	142
$y \Rightarrow$		*Target Price*		
Treated × *Post*	0.023	0.114*	0.026	−0.129***
	(0.042)	(0.057)	(0.046)	(0.037)
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	
Obs. (Analyst Report-Cohort Level)	19,373	2,061	15,706	1,606
Number of Unique Analysts	546	183	499	159
Number of Unique Firms	1,052	126	820	106
$y \Rightarrow$		*Report Tone*		
Treated × *Post*	0.003	0.066*	0.004	−0.062***
	(0.010)	(0.034)	(0.013)	(0.021)
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	
Obs. (Analyst Report-Cohort Level)	59,992	6,761	46,925	6,306
Number of Unique Analysts	698	273	662	239
Number of Unique Firms	1,387	174	1,069	144

Notes: This table reports the results from replicating our main findings (i.e., Tables 4, 6, 7, and 11) using a subsample limited to analyst reports issued by analysts who reside in a different city from the covered firm's city. 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 A12. Subsample limited to analyst reports issued for never-treated firms

	(1)	(2)	(3)	(4)
	Full Sample	*Heterogeneity Tests*		
		Green	*Neutral*	*Brown*
$y \Rightarrow$		*Air Pollution Discussed*		
Treated × *Post*	0.032***	0.055	0.008	0.116***
	(0.006)	(0.059)	(0.008)	(0.022)
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	
Obs. (Analyst Report-Cohort Level)	7,904	843	5,525	1,536
Number of Unique Analysts	339	79	287	90
Number of Unique Firms	168	24	117	27
$y \Rightarrow$		*Market Reaction (%)*		
Treated × *Post*	0.334	1.146	0.355	−0.215
	(0.474)	(1.563)	(0.578)	(1.058)
p-value for $\beta_{Green} - \beta_{Neutral} > 0$			0.284	
p-value for $\beta_{Neutral} - \beta_{Brown} > 0$			0.319	
p-value for $\beta_{Green} - \beta_{Brown} > 0$			0.246	
Obs. (Analyst Report-Cohort Level)	6,595	716	4,621	1,258
Number of Unique Analysts	337	79	284	90
Number of Unique Firms	166	24	115	27
$y \Rightarrow$		*EPS Forecast (%)*		
Treated × *Post*	0.150	1.134**	0.134	−0.428**
	(0.092)	(0.454)	(0.098)	(0.195)
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	
Obs. (Analyst Report-Cohort Level)	7,850	840	5,500	1,510
Number of Unique Analysts	339	79	287	90
Number of Unique Firms	167	24	117	26

Table A12 (Continued)

	(1)	(2)	(3)	(4)
	Full Sample	*Heterogeneity Tests*		
		Green	*Neutral*	*Brown*
$y \Rightarrow$		*Recommendation*		
Treated × *Post*	0.017	0.396**	0.029	−0.256*
	(0.045)	(0.149)	(0.034)	(0.136)
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	
Obs. (Analyst Report–Cohort Level)	7,741	818	5,405	1,518
Number of Unique Analysts	338	79	286	90
Number of Unique Firms	167	24	117	26
$y \Rightarrow$		*Target Price*		
Treated × *Post*	−0.013	0.312***	−0.026	−0.389***
	(0.097)	(0.083)	(0.102)	(0.000)
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)		
Obs. (Analyst Report–Cohort Level)	2,286	242	1,717	327
Number of Unique Analysts	203	40	163	43
Number of Unique Firms	124	17	87	20
$y \Rightarrow$		*Report Tone*		
Treated × *Post*	0.018	0.091	0.003	0.034
	(0.020)	(0.065)	(0.027)	(0.044)
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	
Obs. (Analyst Report–Cohort Level)	7,904	843	5,525	1,536
Number of Unique Analysts	339	79	287	90
Number of Unique Firms	168	24	117	27

Notes: This table reports the results from replicating our main findings (i.e., Tables 4, 6, 7, and 11) 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). All variables are defined in the Variable Appendix in the paper or in Table A1. 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 A13. Clustering standard errors at the city level

	(1)	(2)	(3)	(4)
	Full Sample	*Heterogeneity Tests*		
		Green	*Neutral*	*Brown*
$y \Rightarrow$		*Air Pollution Discussed*		
Treated × *Post*	0.022***	0.061**	0.013***	0.050***
	[0.000]	[0.014]	[0.000]	[0.008]
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	
Obs. (Analyst Report–Cohort Level)	67,389	7,353	52,876	7,160
Number of Unique Analysts	715	292	684	257
Number of Unique Firms	1,460	184	1,127	149
$y \Rightarrow$		*Market Reaction (%)*		
Treated × *Post*	−0.121	0.834***	−0.113	−1.185***
	[0.380]	[0.000]	[0.435]	[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	
Obs. (Analyst Report–Cohort Level)	56,393	6,276	44,227	5,890
Number of Unique Analysts	713	291	681	255
Number of Unique Firms	1,448	184	1,117	147
$y \Rightarrow$		*EPS Forecast (%)*		
Treated × *Post*	0.018	0.284***	0.042	−0.440***
	[0.290]	[0.000]	[0.212]	[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	
Obs. (Analyst Report–Cohort Level)	67,071	7,311	52,642	7,118
Number of Unique Analysts	715	291	684	257
Number of Unique Firms	1,458	183	1,127	148

Table A13 (Continued)

	(1)	(2)	(3)	(4)
	Full Sample	*Heterogeneity Tests*		
		Green	*Neutral*	*Brown*
$y \Rightarrow$		*Recommendation*		
Treated × *Post*	0.000	0.152***	0.002	−0.165***
	[0.991]	[0.000]	[0.871]	[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	
Obs. (Analyst Report–Cohort Level)	65,389	7,110	51,218	7,061
Number of Unique Analysts	711	291	680	257
Number of Unique Firms	1,443	183	1,112	148
$y \Rightarrow$		*Target Price*		
Treated × *Post*	0.008	0.137***	0.007	−0.129*
	[0.772]	[0.000]	[0.832]	[0.054]
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	
Obs. (Analyst Report–Cohort Level)	21,705	2,268	17,633	1,804
Number of Unique Analysts	563	198	520	170
Number of Unique Firms	1,113	135	864	114
$y \Rightarrow$		*Report Tone*		
Treated × *Post*	0.001	0.081***	−0.001	−0.063***
	[0.800]	[0.000]	[0.871]	[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	
Obs. (Analyst Report–Cohort Level)	67,389	7,353	52,876	7,160
Number of Unique Analysts	715	292	684	257
Number of Unique Firms	1,460	184	1,127	149

Notes: This table reports the results from replicating our main findings (i.e., Tables 4, 6, 7, and 11) 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. All variables are defined in the Variable Appendix. *, **, *** indicate statistical significance at the 10%, 5%, and 1% levels (two-sided), respectively.

Table A14. Including control variables

	(1)	(2)	(3)	(4)
	Full Sample	*Heterogeneity Tests*		
		Green	*Neutral*	*Brown*
$y \Rightarrow$		*Air Pollution Discussed*		
Treated × *Post*	0.023***	0.060**	0.014***	0.056***
	(0.005)	(0.024)	(0.002)	(0.017)
Following History	−0.010*	−0.011	−0.007**	−0.032***
	(0.006)	(0.039)	(0.003)	(0.011)
Experience	0.013***	0.076	0.005	0.017
	(0.004)	(0.053)	(0.005)	(0.051)
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	
Obs. (Analyst Report–Cohort Level)	67,389	7,353	52,876	7,160
Number of Unique Analysts	715	292	684	257
Number of Unique Firms	1,460	184	1,127	149
$y \Rightarrow$		*Market Reaction (%)*		
Treated × *Post*	−0.136	0.822**	−0.121	−1.281***
	(0.198)	(0.389)	(0.227)	(0.413)
Following History	0.115	0.091	0.084	0.316
	(0.149)	(0.365)	(0.168)	(0.860)
Experience	0.052	0.737	−0.096	0.976
	(0.163)	(0.707)	(0.221)	(0.932)
p-value for $\beta_{Green} - \beta_{Neutral} > 0$			0.008	
p-value for $\beta_{Neutral} - \beta_{Brown} > 0$			0.007	
p-value for $\beta_{Green} - \beta_{Brown} > 0$			0.000	
Obs. (Analyst Report-Cohort Level)	56,393	6,276	44,227	5,890
Number of Unique Analysts	713	291	681	255
Number of Unique Firms	1,448	184	1,117	147

Table A14 (Continued)

	(1)	(2)	(3)	(4)
	Full Sample	*Heterogeneity Tests*		
		Green	*Neutral*	*Brown*
$y \Rightarrow$		*EPS Forecast (%)*		
Treated × *Post*	0.020	0.265***	0.047	−0.450***
	(0.021)	(0.094)	(0.032)	(0.125)
Following History	−0.003	0.170**	−0.032	0.059
	(0.038)	(0.068)	(0.034)	(0.110)
Experience	−0.043*	−0.055	−0.036	−0.103
	(0.024)	(0.095)	(0.030)	(0.285)
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	
Obs. (Analyst Report–Cohort Level)	67,071	7,311	52,642	7,118
Number of Unique Analysts	715	291	684	257
Number of Unique Firms	1,458	183	1,127	148
$y \Rightarrow$		*Recommendation*		
Treated × *Post*	−0.005	0.144**	−0.002	−0.166***
	(0.019)	(0.055)	(0.019)	(0.037)
Following History	0.035*	0.079	0.034*	0.010
	(0.018)	(0.077)	(0.019)	(0.071)
Experience	−0.019	−0.046	−0.020	0.005
	(0.027)	(0.106)	(0.028)	(0.055)
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	
Obs. (Analyst Report–Cohort Level)	65,389	7,110	51,218	7,061
Number of Unique Analysts	711	291	680	257
Number of Unique Firms	1,443	183	1,112	148

Table A14 (Continued)

	(1)	(2)	(3)	(4)
	Full Sample	*Heterogeneity Tests*		
		Green	*Neutral*	*Brown*
$y \Rightarrow$		*Target Price*		
Treated × *Post*	0.002	0.095	−0.002	−0.126**
	(0.034)	(0.082)	(0.037)	(0.050)
Following History	0.063	−0.146	0.086	0.010
	(0.047)	(0.119)	(0.057)	(0.124)
Experience	−0.028	−0.057	−0.040	0.103
	(0.095)	(0.088)	(0.121)	(0.179)
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	
Obs. (Analyst Report–Cohort Level)	21,705	2,268	17,633	1,804
Number of Unique Analysts	563	198	520	170
Number of Unique Firms	1,113	135	864	114
$y \Rightarrow$		*Report Tone*		
Treated × *Post*	−0.003	0.077***	−0.005	−0.066***
	(0.010)	(0.027)	(0.013)	(0.014)
Following History	0.031*	0.031	0.033	0.019
	(0.017)	(0.042)	(0.021)	(0.021)
Experience	−0.009	0.034	−0.019	0.041
	(0.012)	(0.047)	(0.012)	(0.034)
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	
Obs. (Analyst Report–Cohort Level)	67,389	7,353	52,876	7,160
Number of Unique Analysts	715	292	684	257
Number of Unique Firms	1,460	184	1,127	149

Notes: This table reports the results from replicating our main findings (i.e., Tables 4, 6, 7, and 11) after adding control variables. Control variables include *Following History* and *Experience*. All variables are defined in the Variable Appendix in the paper or in Table A1. 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 A15. Distance between the analyst's city and the covered firm's city

	(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 $\beta_{Yes} - \beta_{No} = 0$	0.317	
Obs. (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-polluting 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. All variables are defined in the Variable Appendix in the paper or in Table A1. 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 B Large Language Model

B.1 Model performance

In this section, we evaluate the performance of the large language models on our three classification tasks. For each task, we draw a random sample and hire two research assistants (RAs) to manually and independently classify each report. For the small number of cases where the two RAs disagree, one of the coauthors reviews the case and makes the final determination. We then assess the model's performance against this benchmark. Following prior research (e.g., Harford et al., 2026; Li et al., 2026), we report four standard classification metrics: (i) accuracy, the proportion of observations correctly classified; (ii) precision, the proportion of true positives among all observations the model classifies as positive; (iii) recall, the proportion of actual positives the model correctly identifies; and (iv) the F1-score, the harmonic mean of precision and recall. Table B1 reports these performance metrics.

B.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 pollution—our *Air Pollution Discussed* variable. We randomly selected 500 analyst reports and hired two RAs to manually and independently classify whether each report discusses air pollution. We find that, out of 500 reports, the model correctly classifies 495: 35 reports identified as discussing air pollution (true positives) and 460 identified as not discussing air pollution (true negatives). The model misclassifies 2 reports as discussing air pollution when they do not (false positives) and 3 reports as not discussing air pollution when they actually do (false negatives).

Column 1 of Table B1 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 pollution in analyst reports. The precision—defined as the proportion of true positives among all reports the model classified as discussing air pollution—is 94.6%. The recall—defined as the proportion of actual air pollution-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 LLMs in different contexts (e.g., Li et al., 2026).

Figure B1 plots the quarterly average of *Air Pollution Discussed* from 2010 to 2015, showing that the share of analyst reports discussing air pollution remained at roughly 2% before 2012, rose steadily during the rollout of the monitoring program, and stabilized at about 6–7% from 2014 onward.

B.1.2. Analyst discussions of different types of environmental risks

In this section, we evaluate the performance of *DeepSeek-R1* in classifying the types of environmental risks discussed in analyst reports. We selected 100 analyst reports that discuss air pollution and hired two RAs to manually and independently classify the type of risk discussed in each report. Columns 2–10 of Table B1 report the results. For brevity, we discuss the two broad categories: physical and transition risks. For physical risks, the model correctly classifies all 100 reports: 7 reports identified as discussing physical risks (true positives) and 93 identified as not discussing physical risks (true negatives). Precision, recall, and F1-score are each 100% (Column 2). For transition risks, the model correctly classifies 98 of the 100 reports: 90 reports identified as discussing transition risks (true positives) and 8 identified as not discussing transition

risks (true negatives). The model misclassifies 1 report as discussing transition risks when it does not (false positive) and 1 report as not discussing transition risks when it actually does (false negative). Precision, recall, and F1-score are each 98.9% (Column 3). Columns 4–10 report the results for the components of transition risk, with accuracy of at least 95% for each component.

B.1.3. Brown, Neutral, Green

In this section, we evaluate the performance of *DeepSeek-Reasoner* for classifying firms as brown, neutral, or green. We randomly selected 100 annual reports from the 1,460 firms covered by analyst reports in our sample. Two 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 find that, 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). Column 11 of Table B1 reports standard classification metrics to evaluate the model's performance, focusing on brown firms. The results indicate that *DeepSeek-Reasoner* is highly reliable, accurately classifying 98% of the firms. The precision, recall, and F1-score are 93%. Columns 12 and 13 report similar performance for neutral and green firms.

B.2 Choice of language model

We choose *DeepSeek-R1* over other large language models (e.g., *GPT-4o, Claude Opus 4*) 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 remain on our internal systems. In contrast, most proprietary models (e.g., *GPT-4o*) 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*. 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.

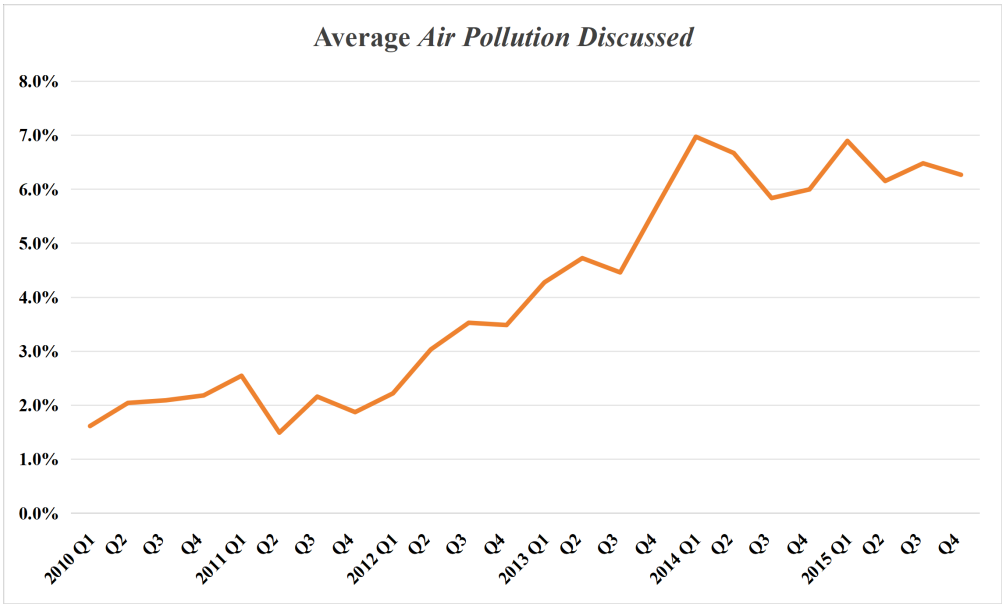
Cost: The cost of using *DeepSeek* is limited to computational infrastructure, as the model is open-source and can be run locally. In contrast, proprietary models are typically accessed via paid APIs, where charges accumulate based on the number of tokens processed. These per-token costs can be substantial, particularly in our setting, where we extract multiple outputs from each report: whether air pollution is discussed, whether social capital is discussed, and the types of risks discussed.

References

Harford, J., He, Q., and Qiu, B. (2026). Firm-level labor shortage exposure. *The Review of Financial Studies*. Forthcoming.

Li, K., Mai, F., Shen, R., Yang, C., and Zhang, T. (2026). Dissecting corporate culture using generative ai. *The Review of financial studies*, 39(1):253–296.

Figure B1. Time trend in *Air Pollution Discussed* measure



Notes: This figure presents the trend in the average of our *Air Pollution Discussed* measure. *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*).

Table B1. *DeepSeek* classification performance

	Report classification										Firm classification		
Metric	*Air Pollution Discussed* (1)	*Physical Risks* (2)	*Transition Risks* (3)	*Regulatory Risks* (4)	*Preference Factors* (5)	*Stakeholder Risks* (6)	*Current Regulatory Risks* (7)	*Future Regulatory Risks* (8)	*Current Preference Factors* (9)	*Future Preference Factors* (10)	*Brown* (11)	*Neutral* (12)	*Green* (13)
Accuracy	99.0%	100.0%	98.0%	99.0%	96.0%	99.0%	96.0%	99.0%	95.0%	99.0%	98.0%	97.0%	99.0%
Precision	94.6%	100.0%	98.9%	98.9%	98.5%	75.0%	98.7%	98.6%	98.3%	98.5%	93.3%	96.9%	100.0%
Recall	92.1%	100.0%	98.9%	100.0%	95.6%	100.0%	96.3%	100.0%	93.7%	100.0%	93.3%	98.4%	95.2%
F1 Score	93.3%	100.0%	98.9%	99.4%	97.0%	85.7%	97.5%	99.3%	95.9%	99.2%	93.3%	97.7%	97.6%

Notes: This table presents the performance metrics of the two large language models we use to construct our text-based measures: *DeepSeek-R1*, which we use to identify whether an analyst report discusses air pollution (our *Air Pollution Discussed* variable) and to classify the types of environmental risks discussed in the report, and *DeepSeek-Reasoner*, which we use to classify firms as green, brown, or neutral. For Column 1, 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 types of environmental risks (Columns 2–10), we selected 100 analyst reports that discuss air pollution, and two RAs manually and independently classify the type of risk discussed. In the *Regulatory Risks* column, for instance, a report is positive if it discusses regulatory risks and negative if it does not, regardless of whether it discusses other risk types. For the firm classification (Columns 11–13), 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 these benchmarks. Specifically, we measure the following metrics.

$$\text{Accuracy} = \frac{\text{TP} + \text{TN}}{\text{TP} + \text{TN} + \text{FP} + \text{FN}} \qquad \text{Precision} = \frac{\text{TP}}{\text{TP} + \text{FP}} \qquad \text{Recall} = \frac{\text{TP}}{\text{TP} + \text{FN}} \qquad \text{F1 Score} = 2 \times \frac{\text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}}$$

In each column, an observation is positive if it belongs to the column's category (e.g., a report that discusses air pollution) and negative otherwise. TP is true positives, TN is true negatives, FP is false positives, and FN is false negatives.

Internet Appendix C Examples of air pollution discussions in analyst reports

Example C1. 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 text: 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 C2. 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 (Monitoring program implementation date: 27-Jun-2012)

Chinese text: 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 oxides, 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 is 4.95 billion yuan.

Example C3. 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 text: 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 C4. 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 text: 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 C5. 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: Huachuang Securities)
- **City**: Beijing (Monitoring program implementation date: 21-Jan-2012)

Chinese text: 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 C6. Stakeholder 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 (Broker: Guotai Junan Securities)
- **City**: Shanghai (Monitoring program implementation date: 27-Jun-2012)

Chinese text: 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 of 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.