Seeing Is Not Believing: Strategic Pollution Suppression Around Corporate Site Visits

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Abstract

This study examines whether firms strategically "clean up" emissions when investors are watching. Using daily facility-level satellite data from China, we find that manufacturing firms temporarily suppress pollution emissions specifically during investor site visits. The effect is most pronounced among pollution-intensive, high-valuation, and well-governed firms, and is primarily driven by the scrutiny of existing shareholders. Further analysis reveals that firms achieve this reduction by temporarily ramping up abatement equipment rather than suspending production. These findings document a novel form of real activity management where physical signals are endogenously distorted, highlighting the limitations of observed ESG diligence.

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1. Introduction

Financial markets rely heavily on corporate disclosures to assess firm value, yet these reports are inherently composed of “soft” information—accounting numbers and managerial narratives subject to manipulation, accrual management, and positive spin (e.g., Dechow *et al.*, 1995; Sloan, 1996; Huang *et al.*, 2013). To pierce this veil of reported numbers, sophisticated investors increasingly rely on private interactions, with corporate site visits serving as a prevalent practice of due diligence (Bowen *et al.*, 2018; Cheng *et al.*, 2019; Zhang *et al.*, 2025). By touring factories, inspecting inventory, and observing production lines firsthand, investors seek to acquire “hard” information—verifiable, physical evidence of a firm’s operational health that is assumed to be difficult, if not impossible, to fake (Han *et al.*, 2018). The prevailing consensus is that “seeing is believing”: direct observation reduces information asymmetry by allowing investors to observe the “ground truth” of the firm (see Cheng *et al.*, 2016).

This study challenges that consensus. We posit that the physical reality observed by investors is not an immutable truth, but an endogenous signal strategically managed by the firm. Drawing on the concept of the “observer effect”—where the act of observation alters the state of the system being observed (Landsberger, 1958)—we hypothesize that firms actively manipulate their physical environment in anticipation of investor scrutiny. Specifically, we examine whether manufacturing firms temporarily suppress pollution emissions during scheduled investor site visits to create a favorable, albeit transient, impression of environmental and operational quality.

Pollution emissions serve as a highly visible proxy for environmental compliance and ESG (environmental, social, and governance) performance. If firms successfully “stage” their physical operations for visiting investors, the implications for financial markets are profound. This suggests that the “hard” information acquired during site visits is subject to the same “signal jamming” dynamics as financial reports (Stein, 1989), but with a crucial difference:

while earnings management leaves an audit trail, physical signal manipulation is often ephemeral and leaves no record in the financial statements. Documenting this behavior would reveal a new dimension of real activity management and suggest that the information advantage attributed to site visits (Bowen *et al.*, 2018) may, in part, reflect successful deception rather than the discovery of intrinsic value.

Testing this signal manipulation has historically been impossible due to a lack of precise records on private corporate interactions and high-frequency data on physical firm outputs. We overcome this hurdle by combining the mandatory disclosure of site visits in China with high-resolution satellite data that tracks daily air pollution concentrations at the facility level. China offers an ideal laboratory for this investigation for three reasons. First, the Shenzhen Stock Exchange (SZSE) mandates that listed firms disclose the precise timing and attendees of investor site visits within two trading days, providing a rare window into private information acquisition events. Second, the manufacturing sector dominates the Chinese market, making physical operations and their environmental byproducts (emissions) a primary focus of due diligence. Third, unlike financial data which is reported quarterly, pollution is a continuous physical flow that can be measured daily via remote sensing, allowing us to detect transient strategic behavior that standard accounting metrics would miss.

We construct a novel facility-level panel covering 2,366 manufacturing sites from 2012 to 2019, linking 30,948 distinct site visits to daily measures of PM2.5 concentrations derived from the China High Air Pollutants (CHAP) dataset. Using a tight event-study design that controls for city-by-day fixed effects (absorbing local weather and regional pollution trends) and site fixed effects (absorbing time-invariant facility characteristics), we isolate the idiosyncratic variation in pollution specifically attributable to the visited facility during the visit window.

Our baseline analysis reveals stark pollution suppression: local PM2.5 concentrations at a firm's production site drop significantly—by approximately 16% relative to the sample mean—precisely when investors are present. This corresponds to a decline in abnormal pollution of roughly 0.02 μg/m^3 against a sample mean of 0.09 μg/m^3.

The temporal pattern of this reduction creates a distinct "V-shaped" trajectory. Pollution levels are normal in the week preceding the visit, drop sharply beginning two days before the visit, remain their nadir on the visit day, and rebound to baseline levels immediately thereafter. This transient pattern is inconsistent with structural improvements in environmental performance or adoption of cleaner technologies. Instead, it bears the hallmarks of strategic suppression—the firm cleans up its visible operations solely for the duration of the external inspection (Duflo *et al.*, 2013). Furthermore, this strategic suppression increases with visit intensity and is more pronounced when the visitors are key institutional investors—such as mutual funds, asset management companies, and securities firms—whose assessments likely carry greater weight in the capital markets.

We employ a series of placebo tests to confirm that this phenomenon is driven by the *physical presence* of the monitor. We find no such pollution reduction during "online visits" (teleconferences), nor do we observe changes at the firm's non-visited "sister" facilities located in the same or different cities. These non-results rule out the possibility that our findings are driven by firm-wide news, coincident policy changes, or general investor attention. The pollution drop occurs only when, and exactly where, the investors are physically walking the ground.

We next investigate *who* engages in this manipulation and *why*. First, consistent with a risk-mitigation motive, we find that the strategic suppression of pollution is significantly stronger for firms in pollution-intensive industries and those with poor environmental ESG ratings (low "E"), where the cost of being caught "dirty" is highest. Second, regarding corporate value and control, standard agency theory might suggest that such deceptive practices are the province of “bad” firms—those with poor governance, entrenched management, or low market value—attempting to mask their incompetence (see Shleifer and Vishny (1997)). However, our results reveal a more nuanced and counter-intuitive reality: the strategic suppression of pollution is most pronounced among firms with high market valuations and strong corporate governance.

Specifically, we find that physical signal manipulation is most prevalent among firms with high Tobin’s Q, high governance ESG ratings (high “G”), high institutional ownership, and low management entrenchment (i.e., managers are less likely to be paid excessively). We argue that this behavior reflects a rational alignment of incentives between managers and current shareholders, rather than a failure of oversight. Managers subject to strict discipline are acutely aware that allowing visitors to witness pollution could expose operational weaknesses and damage firm valuation. Consequently, they are likely to be more “jittery” regarding upcoming visits, creating a strong incentive to execute preemptive cleanups to protect their careers and shareholder value. Furthermore, for high-valuation firms, the marginal cost of a negative signal is severe; a “dirty” site visit could puncture the growth narrative and lead to a sharp repricing of the stock. Consequently, managers of these firms are highly incentivized to protect the stock price by ensuring the visit goes smoothly. Thus, we interpret this “greenwashing” not necessarily as an agency cost (management misconduct), but as a sophisticated form of real activity management where disciplined managers actively manage signals to maximize shareholder value during high-stakes monitoring events.

We further disentangle the mechanism by distinguishing between an “ownership channel” and a “reputation channel.” One might hypothesize that firms clean up to appeal to environmentally conscious investors or to avoid backlash from ESG-focused funds. However, we find that visits by Principles for Responsible Investment (PRI) signatories—who ostensibly care most about environmental issues—do not trigger differential pollution reductions. Instead, the effect is driven almost entirely by visits from existing shareholders. This supports an ownership-monitoring hypothesis: managers are acutely sensitive to the scrutiny of those who hold the voting power and the ability to exit. When the owners come to inspect the asset, the managers ensure the asset looks pristine.

Finally, we investigate the operational means by which this signal manipulation is achieved. Does the firm shut down the factory to reduce smoke, thereby sacrificing economic output? Or do they decouple emissions from production? Using satellite-derived thermal infrared (TIR) data as a proxy for heat generation and factory activity (Xue *et al.*, 2025), we find no evidence of production suspension. Thermal output remains constant during the visit window even as pollution falls. Instead, we find the effect is concentrated in firms with high installed abatement capacity (e.g., scrubbers, filters). This suggests a sophisticated strategy: firms temporarily ramp up costly abatement technologies—which might otherwise be idled to save costs—to “sanitize” the air without disrupting production. This is the environmental equivalent of “channel stuffing” or cutting R&D to meet an earnings target: a real economic action taken to distort the observable signal of performance.

This study makes three distinct contributions to literature. First, we advance the literature on information acquisition and corporate site visits (Cheng *et al.*, 2016; Bowen *et al.*, 2018; Han *et al.*, 2018; Cheng *et al.*, 2019; Zhang *et al.*, 2025). Prior work largely treats the firm as a passive object of study, assuming that proximity leads to truth. We demonstrate that the firm is an active strategic agent. By documenting the endogeneity of “hard” information, we show that the very act of monitoring induces a distortion in the parameter being monitored. Thus, in the context of physical site visits, our evidence suggests that “seeing is not believing.” This implies that the positive abnormal returns associated with site visits documented in prior literature may need to be re-evaluated; they may reflect not just the discovery of undervalued firms, but the successful management of investor perceptions.

Second, we contribute to the literature on corporate governance and real earnings management (Roychowdhury, 2006; Cohen & Zarowin, 2010; Gunny, 2010; Zang, 2012). The literature typically focuses on financial variables such as product pricing and discretionary expenses. We document a novel form of real activity signal jamming involving physical externalities. Moreover, our findings—that high-quality firms are the most aggressive manipulators—challenge the simplistic view that governance always promotes transparency. We show that when transparency threatens valuation, strong governance can enforce strict discipline in executing signal manipulation.

Third, we bridge the gap between environmental economics and finance. Recent research in environmental economics demonstrates that regulated entities respond strategically to intermittent and spatially limited monitoring. For instance, Zou (2021) shows that U.S. polluters suppress emissions on days when government monitors are scheduled, resulting in worse air quality on unmonitored days—a phenomenon characterized as "unwatched pollution". Similarly, Yang *et al.* (2024) and Grainger *et al.* (2019) find that local officials concentrate abatement efforts near monitoring stations or site monitors in cleaner locations to avoid detection. We extend this framework of strategic compliance to the capital markets. This distinction is critical because, unlike regulators who enforce compliance, investors seek accurate pricing information. Our results suggest that the current reliance on episodic "on-the-ground" ESG due diligence could be flawed. If firms can simply "turn on the scrubbers" when the analyst arrives, then distinct, physical visits are poor proxies for persistent environmental performance. This underscores the necessity of continuous, third-party data (like satellite monitoring) in modern asset pricing and ESG integration, as "unwatched" pollution likely represents the firm's true type.

The remainder of the paper proceeds as follows. Section 2 describes the research background and develops the hypothesis. Section 3 details the data, variable construction, and empirical design. Section 4 presents the main results. Section 5 examines heterogeneity and mechanisms. Section 6 provides additional analyses, and Section 7 concludes.

2. Research background and hypothesis

2.1. Research background

2.1.1. Investor information acquisition and corporate site visits

In-person meetings between investors and firms serve as a critical information channel in financial markets (Brown *et al.*, 2015), yet data on such interactions have historically been unavailable. In 2012, the SZSE addressed this limitation by requiring listed companies to disclose site visits on its "Hu Dong Yi" portal (http://irm.cninfo.com.cn/) within two trading days. This regulation provides a novel data source for observing such activity. Typically, these visits involve investors touring physical premises to gather operational insights. Although hosting visits is voluntary, firms are encouraged to accommodate these requests to enhance transparency with market participants.

Cheng *et al.* (2016), analyzing the early years of these disclosures, find that analysts who conduct site visits subsequently improve their earnings forecast accuracy relative to non-visiting peers. This suggests that site visits enable analysts to observe operational details and gather both "hard" and "soft" information, yielding an informational advantage.

Subsequent research documents additional implications. Bowen *et al.* (2018) report that corporate insiders conduct a significant portion of their informed stock trades after hosting private meetings, effectively profiting from the information revealed to select outsiders. Cheng *et al.* (2019) find that stock returns begin to drift upward prior to earnings announcements when a site visit has recently occurred, interpreting this as the capitalization of positive private signals. Similarly, Zhang *et al.* (2025) show that an abnormal frequency of site visits predicts superior stock returns, indicating that visits help investors identify mispriced firms. Furthermore, site visits are found to influence firm performance: more frequent visits correlate with lower earnings manipulation (Qi *et al.*, 2021) and improved investment efficiency (Cao *et al.*, 2025), suggesting that managers respond to the scrutiny of informed outsiders.

While this literature establishes site visits as valuable events for private information production, it largely treats the firm as a passive subject. Prior research has not fully considered that the firm might deliberately alter its behavior or environment in anticipation of a visit. We address this gap by integrating the site visit literature with the concept of strategic compliance. We posit that site visits are not merely information-revealing events but are endogenously influenced by firm actions. Specifically, we investigate whether the environmental information observed by investors is strategically managed by the host.

2.1.2. Remote sensing and pollution data advances

A primary challenge in detecting strategic environmental behavior is measurement, as pollution can be displaced across time or space to evade observation. Recent advances in satellite remote sensing have significantly enhanced the ability to observe pollution continuously and at fine spatial scales. For example, Currie *et al.* (2023) leverage satellite-derived PM2.5 concentration data at a 0.01 × 0.01-degree resolution (from Di *et al.* (2016)) to measure individual exposure levels across the United States. By linking these granular measures with demographic and regulatory data, they show that the 1990 Clean Air Act amendments disproportionately benefited Black communities, accounting for over 60% of the convergence in Black–White pollution exposure gaps. Such studies underscore the power of high-resolution data to uncover demographic patterns that would remain undetected with sparse ground monitors.

Satellite data have also been employed to identify monitoring evasion. Grainger *et al.* (2019) combine NASA Aerosol Optical Depth data with ground monitor readings to identify unmonitored areas with high pollution, providing evidence that some U.S. counties avoided placing monitors in the most polluted locations. Likewise, Zou (2021) uses satellite-based readings on non-monitored days to quantify the increase in smog when regulators were not "watching." In China, nationwide satellite PM2.5 data have allowed researchers to validate ground station reports. Yang *et al.* (2024) employ a spatial difference-in-differences approach using satellite data to demonstrate that monitor-focused cleaning led to a 3.2% drop in particulate levels near monitors—an effect not mirrored citywide.

Our study utilizes the high-resolution CHAP dataset to detect short-duration, localized pollution changes at the firm level. Historically, data limitations precluded such analysis, as firm emissions were unobservable without adjacent official monitors. By leveraging granular satellite data, our work aligns with a broader trend in environmental economics that employs advanced measurement technologies (e.g., satellite sensors and dense monitor networks) to reveal previously hidden forms of pollution issues (e.g., Sullivan and Krupnick (2018) and Fowlie *et al.* (2019)). Crucially, the strategic behavior we document persists despite this increased transparency, underscoring the adaptability of firms in signaling compliance.

2.2. Hypothesis

Building on the preceding discussion, we develop our main hypothesis regarding firm behavior around investor site visits.

Prior literature in environmental economics establishes that regulated entities often game monitoring regimes to meet targets or avoid detection. For instance, polluters temporarily suppress emissions on days when government monitors are scheduled (Zou, 2021) or concentrate pollution control efforts solely in the immediate vicinity of monitoring stations (Yang *et al.*, 2024), effectively "shifting" pollution to periods or locations where it is less likely to be recorded. These findings demonstrate that firms possess both the capacity and the incentive to alter their physical environment in response to external oversight.

We posit that this strategic adaptability extends to informal monitoring by capital market participants. Firms face a strategic tension regarding site visits. On one hand, hosting investors creates significant value: site visits are associated with enhanced transparency, which can improve firm valuation and lower the cost of capital (Cheng *et al.*, 2016; Zhang *et al.*, 2025). Consequently, managers have strong incentives to accommodate visit requests. On the other hand, the physical nature of these interactions exposes operations to direct observation, potentially revealing negative externalities that firms wish to conceal.

To resolve this conflict between the desire to host investors and the need to hide poor environmental performance, we theorize that firms will engage in temporary remediation. When a firm anticipates an investor visit, it will take short-term actions to improve visible environmental conditions—a form of physical "window dressing." This behavior stems from an impression management or "signal jamming" motive: managers understand that visitors will scrutinize details otherwise hidden from the market, prompting proactive efforts to shape the firm's presentation.

Environmental performance is particularly visible during a facility tour. Smoke, dust, and odors provide immediate, tangible signals of pollution management quality. Because these environmental cues are salient to anyone walking through a plant, they are prime targets for manipulation. A manager expecting a visit has a strong incentive to temporarily curtail polluting activities and ensure environmental indicators appear favorable while investors are present. Accordingly, we formulate our central hypothesis:

Hypothesis 1: Firms strategically reduce their pollution emissions during periods when investors conduct on-site visits.

3. Methodology

3.1. Sample and data sources

Our study focuses on manufacturing firms listed on the SZSE from January 1, 2012, to

December 31, 2019.[1] We restrict our sample to the manufacturing sector for both physical and informational reasons. Physically, manufacturing operations represent significant sources of industrial emissions, providing a setting where strategic abatement is potentially detectable (Shapiro & Walker, 2018). Informationally, the value of site visits is contingent on the observability of operations. Cheng *et al.* (2016) document that the positive effect of site visits on analyst forecast accuracy is significantly stronger for firms in manufacturing industries, particularly those with higher asset tangibility. For these entities, direct observation of production lines, inventory levels, and factory conditions allows visitors to gather valuable "hard" information.

A single publicly listed firm typically operates multiple distinct subsidiaries, factories, or production facilities dispersed across different geographic locations. Our analysis is conducted at the site level, allowing us to exploit variation in pollution dynamics specific to each individual facility.

To construct our site-level dataset, we first identify the universe of subsidiaries and production plants associated with SZSE-listed manufacturing firms. Data on facility addresses and ownership structures are obtained from the *Controlled & Participated Company Database of Listed Companies* (CPCD) provided by the Chinese Research Data Services (CNRDS). We include plants where the listed firm holds at least 50% control. For each facility, we obtain the exact geographic coordinates (latitude and longitude).

We utilize the CHAP dataset to measure local air pollution. This dataset provides seamless, high-resolution ground-level PM2.5 concentrations (Wei *et al.*, 2021). We overlay the coordinates of our identified sites with these daily pollution grids to extract site-specific air quality measures.

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[1] The sample period begins in 2012, coinciding with the implementation of the SZSE's disclosure requirement for site visits. We end the sample in 2019 to exclude the confounding effects of the COVID-19 pandemic and associated travel restrictions, consistent with recent literature (e.g., Zhang *et al.*, 2025).

We combine this spatial and pollution data with site visit records from the "Records of Investor Relations Activities" in the China Stock Market & Accounting Research (CSMAR) database. We identify site visits based on the "meeting method" field, manually reviewing records to confirm physical tours.[2] To link these visits to specific geographic locations, we review the meeting records for address details. If the disclosure specifies a particular facility or subsidiary location, we map the visit to that specific site. If the information provided is insufficient to identify a specific site location, we assume the visit occurred at the firm's headquarters. Merging these datasets with firm-level financial characteristics results in a final sample of 2,366 distinct geographic sites associated with 1,350 unique manufacturing firms. We restrict the sample to sites that received at least one visit during the sample period to ensure valid treatment variation. The distribution across manufacturing sub-industries is reported in Table IA1 of the Internet Appendix.[3]

Figure 1 illustrates the geographic distribution of sites in our sample alongside visit frequency. Consistent with the broader population of listed Chinese firms, sites are concentrated in coastal regions and provincial capitals. Visit intensity varies considerably: while the vast majority (approximately 95%) of sites received fewer than 50 visits, a small subset of highly visible locations hosted over 250 visits. The final panel comprises approximately 6.9 million (*i.e.*, 2,366 sites × 365 days × 8 years = 6,908,720) site-day observations covering 30,948 distinct site visit events, with each site receiving an average of 13 visits during the sample period.

[Insert Figure 1 about here]

3.2. Variable construction

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[2] We manually review each original record and remove conference calls, roadshows, and communications conducted by phone, video, or email, ensuring our analysis focuses exclusively on face-to-face site visits to firms' plants or headquarters.

[3] The total frequency is 1,414—larger than the number of unique firms—because some firms change their industries during our sample period.

3.2.1. Measuring local air pollution

The CHAP dataset is generated using machine learning algorithms that integrate ground-based measurements of pollutants, satellite remote sensing products, and atmospheric reanalysis data (Wei *et al.*, 2020; Wei *et al.*, 2021). This dataset provides daily 1 km ground-level PM2.5 data for China from 2000 to the present.[4] The dataset exhibits high quality, with a cross-validation coefficient of determination (CV - R^2) of 0.90 on a daily basis (Wei *et al.*, 2021).

[Insert Figure 2 about here]

Using this high-resolution grid, we construct two site-specific pollution measures as visualized in Figure 2. The first measure, raw level of pollution ($Pollutioni_{i,j,t}$), represents the average ambient pollution exposure at the production facility. It is defined as the average PM2.5 concentration ($\mu g/m^3$) within a 1-kilometer radius (the red inner circle in Figure 2) centered on site i in city j on day t. The definition is provided in Appendix 1.

The second measure, abnormal pollution ($Pollution^{abn}_{i,j,t}$), is designed to isolate idiosyncratic emission changes attributable to the specific site from broader regional trends. We calculate the difference between the pollution level in the immediate vicinity of the site and the surrounding area. Specifically, this variable is defined as the difference between the average PM2.5 concentration within the 1km inner circle ($Pollution_{i,j,t}$) and the average concentration in the surrounding 1 km to 3 km annular ring ($Pollution^{ring}_{i,j,t}$) (the blue area in Figure 2). This spatial difference-in-differences approach effectively nets out background pollution—such as city-wide smog or weather-driven variations—allowing us to isolate idiosyncratic emission changes attributable to the specific site.

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[4] This measure offers the highest spatial resolution currently utilized in the economics literature. For comparison, Currie *et al.* (2023) use PM2.5 concentrations at a 0.01-degree by 0.01-degree resolution to study the Black-White gap in pollution exposure, while Zou (2021) uses aerosol concentrations at a 10km×10km resolution to examine the impact of monitoring on pollution emissions.

$$Pollution_{i,j,t}^{abn} = Pollution_{i,j,t} - Pollution_{i,j,t}^{ring} \quad (1)$$

3.2.2. Identifying site visit events

Unlike remote forms of corporate communication, such as conference calls, site visits allow market participants—including investors, analysts, and fund managers—to directly tour operational facilities. Underscoring the importance of this channel, recent research indicates that China's top mutual fund firms allocate 40-50% of their working hours to these visits (Zhang *et al.*, 2025).

The "Records of Investor Relations Activities" from the CSMAR database provides detailed information for each site visit, including the date, participants, firm management who participated, and the meeting minutes. We utilize this granular data to construct our primary independent variables. We define a binary variable, $SiteVisit_{i,j,t}$, which equals one if site i receives a visit on day t, and zero otherwise. To capture the potential anticipatory or lagged effects of the visit, we also construct an indicator $SiteVisit_{i,j,t}^{3d}$, which equals one if site i receives a visit within a 3-day window (i.e., day t, day t-1, or day t+1). This window accounts for the immediate period surrounding the event where operational adjustments might occur.

Appendix 2 details the distribution of visitor types across our 30,948 visits. The participants are diverse, comprising securities firms (e.g., investment bank/brokerage), funds, asset management companies, foreign institutions (e.g., QFII), insurance companies, banks, investment advisors, media, and individual investors. A single visit can involve multiple visitor types simultaneously (e.g., a joint visit by analysts and fund managers). Securities firms participate in 80% of the visits in our sample, followed by funds (62%) and asset management companies (42%).

3.3. Empirical model

3.3.1. Baseline model

To estimate the impact of site visits on local pollution, we employ the following specifications:

$$Y_{i,j,t} = \alpha + \beta \times VisitEvent_{i,j,t} + \gamma \times X_{i,j,t} + \eta_i + \mu_{j,t} + \varepsilon_{i,j,t} \qquad (2)$$

where the dependent variable $Y_{i,j,t}$ represents either the raw pollution level (*Pollution*) or the abnormal pollution level ($Pollution^{abn}$). $VisitEvent_{i,j,t}$ represents the variable of interest, which can be either the single-day indicator $SiteVisit_{i,j,t}$ or the three-day window indicator $SiteVisit_{i,j,t}^{3day}$, depending on the specification.

We include a vector of controls, $X_{i,j,t}$, to account for site-specific characteristics and localized environmental conditions. Specifically, we control for $Pollution_{i,j,t}^{lag}$, the average pollution level at site *i* over the window [t-14, t-7]. This variable captures the persistence of site-specific emission levels prior to the immediate event window, accounting for operational continuity and previous environmental performance. Additionally, we include $Pollution_{i,j,t}^{ring}$, the concurrent pollution level in the 1km-3km buffer zone surrounding the site. Controlling for the pollution in this ring area is crucial as it represents the background pollution level in the immediate vicinity, driven by broader regional factors such as weather patterns or city-wide emissions.

We further include site fixed effects (η_i) to absorb time-invariant site characteristics (e.g., industry type, production capacity, geography) and city-by-date fixed effects ($\mu_{j,t}$) to absorb time-varying shocks common to a city on a given day, such as meteorological conditions (wind, precipitation, temperature) and city-wide pollution trends. Consequently, the coefficient β identifies the idiosyncratic pollution variation at a specific site during a visit, relative to the same site on days without visits and to other sites in the same city on the same day. Standard errors are clustered at the site level to account for serial correlation in errors within sites over time.

3.3.2. Dynamic model

To examine the temporal dynamics of pollution and test for pre-existing trends, we estimate the following specification:

$$Y_{i,j,t} = \alpha + \sum_{n=-7}^{7} \beta_n \times VisitWindow_{i,j,t+n} + \gamma \times X_{i,j,t} + \eta_i + \mu_{j,t} + \varepsilon_{i,j,t} \qquad (3)$$

where $VisitWindow_{i,j,t+n}$ is an indicator variable equal to one if site i is visited on day $t + n$. We estimate coefficients for a two-week window ranging from 7 days before (n = -7) to 7 days after (n = 7) the visit. The points outside the 14-day window serve as the reference period. This specification allows us to verify whether pollution reduction is concentrated around the visit dates and ensures that the results are not driven by pre-existing downward trends in emissions.

3.4. Summary statistics

Table IA2 presents the summary statistics for the main variables used in the study. The average PM2.5 concentration (*Pollution*) is 49.57 $\mu g/m^3$, with the surrounding buffer ring ($Pollution^{ring}$) showing a slightly lower average of 49.48 $\mu g/m^3$. The average abnormal pollution ($Pollution^{abn}$) is 0.093 $\mu g/m^3$. The mean of *SiteVisit* is 0.004, meaning that there are 4 observations of sites for every 1,000 site-daily observation points. It increases to 13 if the site event is defined in a window of 3 days (the mean of $SiteVisit^{3day}$ is 0.013).

4. Main results

4.1. Baseline model results

Table 1 presents the estimates of Equation (2). Columns (1) and (2) report the results using abnormal pollution ($Pollution^{abn}$) as the dependent variable, which effectively nets out common regional trends to isolate site-specific emission dynamics. In Column (1), the coefficient on the single-day indicator *SiteVisit* is -0.015 and is statistically significant at the 5% level. This magnitude corresponds to a 16.1% reduction relative to the sample mean (0.093 $\mu g/m^3$). To capture operational adjustments surrounding the event, Column (2) employs the three-day window indicator, $SiteVisit^{3day}$. The estimated coefficient is -0.016 (statistically significant at the 1% level), representing a 17.2% reduction relative to the mean. These findings suggest that firms actively suppress emissions during periods of external monitoring, consistent with the hypothesis of strategic pollution suppression.

[Insert Table 1 about here]

Columns (3) and (4) verify these findings using raw pollution levels (*Pollution*) as the outcome variable. The coefficients remain negative and statistically significant. Specifically, the coefficient on *SiteVisit* in Column (3) is -0.015, statistically significant at the 10% level. Similarly, the coefficient on $SiteVisit^{3day}$ in Column (4) is -0.017, significant at the 1% level. The estimates are quantitatively similar to those based on abnormal pollution, indicating that our findings are robust to the choice of pollution measures. The control variables behave as expected. Lagged pollution ($Pollution^{lag}$) and pollution in the surrounding buffer ring ($Pollution^{ring}$) are highly predictive of site-level pollution, underscoring the importance of the temporal and spatial difference-in-differences design in absorbing baseline missions and regional environmental shocks.

Appendix 3 further disaggregates the baseline specification by visitor type. The results indicate that the strategic abatement effect is driven primarily by key institutional investors, such as asset management companies, funds, and securities firms. For example, the three-day window coefficients in the specifications of abnormal pollution for asset management companies and mutual funds are -0.021 and -0.015, respectively, and both are significant at the 1% level. In contrast, visits by other groups, such as individual investors, media, foreign institutions, or banks, do not yield statistically significant reductions in local pollution. This pattern suggests that managers are particularly sensitive to scrutiny from domestic institutional investors who possess significant capital allocation power and influence over market perceptions.

Collectively, these results provide evidence that manufacturing firms strategically curb pollution emissions during periods of investor oversight.

4.2. Dynamic model results

To further scrutinize the causal interpretation of our findings and map the temporal dynamics of this behavior, we estimate the dynamic model specified in Equation (3). Figure 3 plots the point estimates and 90% confidence intervals for the coefficients on daily indicators ranging from seven days before to seven days after the site visit. Panel A, which displays the results for abnormal pollution, reveals two critical patterns. First, the estimated coefficients for the days leading up to the visit (days t-7 to t-3) are statistically indistinguishable from zero and exhibit no systematic trend. This absence of pre-existing trends supports the parallel trends assumption underlying our identification strategy, suggesting that the observed pollution reduction is not driven by unobserved factors or secular improvements in environmental performance.

Second, there is a sharp and statistically significant decline in pollution beginning two days prior to the visit (t-2) and persisting through the day after the visit (t+1). The effect magnitude peaks within this window before reverting to baseline levels by day t+2. The results based on raw pollution, as shown in Panel B, are qualitatively similar. This “V-shaped” pattern—characterized by a transient dip followed by a quick rebound—is distinct from the permanent pollution reductions typically associated with technological upgrades or persistent regulatory enforcement (Lewis, 2023; Cheng *et al.*, 2025). Instead, it aligns with the “unwatched pollution” phenomenon described in recent literature (Zou, 2021; Karplus & Wu, 2023), where firms strategically ramp down polluting activities when under the direct spotlight of external monitors.

[Insert Figure 3 about here]

4.3. Robustness

We conduct several tests to verify the robustness of our baseline findings, addressing potential concerns regarding chance correlations, visit intensity, selection bias, and sample composition.

4.3.1. Falsification tests

To rule out the possibility that our results are driven by chance, we conduct a falsification test using randomization inference. We generate 1,000 counterfactual samples by randomly permuting the incidence of corporate site visits (*SiteVisit*) across the panel while preserving the original sample structure. We then re-estimate the baseline model for each placebo sample to obtain the distribution of the spurious coefficients and t-statistics. Figure 4 presents the results, plotting the kernel density estimates of the 1,000 placebo coefficients in Panel A and their corresponding t-values in Panel B. The placebo estimates are centered around zero and follow a normal distribution, indicating that randomly assigned visits do not systematically predict pollution fluctuations. In contrast, the actual estimated coefficient and t-value from our baseline model—marked by the vertical red lines—lie in the extreme left tails of their respective distributions, clearly separated from the placebo estimates. This divergence implies that the likelihood of observing our main results by chance is small.

[Insert Figure 4 about here]

4.3.2. Visit intensity

We next examine whether the magnitude of pollution reduction varies with the intensity of the site visit. If the observed pollution suppression is a strategic response to external scrutiny, we expect stronger effects when monitoring intensity is higher. Table 2 reports the results using three alternative measures of visit intensity: the length of the disclosure record filed for a specific site visit event (*Ln(# Word)*), the number of visitors (*Ln(# Researcher)*), and the number of visiting institutions (*Ln(# Institution)*). Across all specifications, the coefficients on these intensity measures are negative and statistically significant. For instance, in Columns (3) and (4), the coefficients on *Ln(# Researcher)* are -0.008 (significant at the 5% level) and -0.007

(significant at the 10% level), respectively, indicating that a larger delegation of visitors is associated with a more pronounced reduction in local air pollution. These findings suggest that firms scale their emission abatement efforts in proportion to the intensity of external monitoring.

[Insert Table 2 about here]

4.3.3. Selection on unobservables

To address the concern that our results may be driven by unobserved factors, we employ the method developed by Oster (2019) to evaluate the potential bias from omitted variables. We calculate the Oster delta statistic, which compares the stability of the coefficient on *SiteVisit* as controls and fixed effects are included. A delta value greater than one (or less than zero) suggests that unobservables do not explain away the estimated treatment effect. Our results in Table IA3 support this conclusion. The calculated delta for the abnormal pollution measure ($Pollution^{abn}$) is 1.11 for the single-day indicator and 1.63 for the three-day window. For the absolute pollution measure (*Pollution*), the delta values are negative (-35.45 and -22.35). These statistics indicate that selection of unobservables seem not to be driver of our main results.

4.3.4. Entropy balancing

To mitigate concerns regarding covariate imbalance between visited and non-visited site-days, we employ entropy balancing, a reweighting technique that matches the covariate distributions of the treatment and control groups on possibly higher moments (Hainmueller & Xu, 2013). This method minimizes model dependence and provides a robust estimate of the treatment effect. Table IA4 presents the results using the reweighted sample. The coefficients on *SiteVisit* and $SiteVisit^{3day}$ remain negative and statistically significant across both abnormal and raw pollution measures. For example, the coefficient on $SiteVisit^{3day}$ in Column (2) is -0.014, quantitatively similar to the baseline estimate of -0.016. These results confirm that our findings are not driven by distributional differences in observable characteristics between the treatment and control groups.

4.3.5. Geographic variation

Finally, we test the sensitivity of our results to various subsample restrictions to ensure our findings are not driven by specific regions with unique regulatory or economic characteristics. Table IA5 reports these robustness checks. Panel A excludes sites located in provincial capitals and municipalities, where regulatory enforcement might be stricter. Panel B excludes southern provinces, and Panel C excludes coastal provinces, which typically exhibit higher economic development and environmental awareness. In all subsamples, the coefficients on *SiteVisit* and $SiteVisit^{3day}$ remain negative and generally significant. This evidence suggests that the phenomenon we document is widespread across China's manufacturing sector and is not confined to specific geographic or economic zones.

5. Heterogeneity and mechanism

To better understand the drivers of the observed strategic abatement, we examine the underlying mechanisms through the lens of industry characteristics, firm valuation, ESG performance, and the specific attributes of the visiting investors.

5.1. Industry pollution intensity

We first examine whether the propensity to manage pollution varies with the firm's industrial environment. Firms in high-pollution industries typically face higher costs—both regulatory and operational—when their emissions are exposed to the public (Buntaine *et al.*, 2024). Because their operations are inherently emission-intensive, they are the primary targets of public outcry and regulatory enforcement when local air quality deteriorates. For instance, when a smog cloud hangs over a region, a coal-power utility is far more likely to face blame and scrutiny than a catering company. Consequently, these firms face heightened incentives to demonstrate "clean" operations during site visits to signal compliance and avoid the severe penalties associated with perceived negligence.

To test this, we classify industries according to the environmental inspection guidelines released by the Ministry of Ecology and Environment of China.[5] We define "High-pollution industries" to include sectors such as thermal power, iron and steel, cement, electrolytic aluminum, coal, metallurgy, chemicals, petrochemicals, building materials, paper, brewing, pharmaceuticals, fermentation, textiles, tanning, and mining. All other sectors are classified as "Low-pollution industries." We investigate the heterogeneity across these sectors by re-estimating the baseline Equation (2) separately for the high-pollution and low-pollution subsamples, allowing us to statistically compare the visit coefficients across groups.

Table 3 reports the results of this heterogeneity analysis. Consistent with our prediction, the strategic reduction in pollution is driven primarily by firms in heavy-polluting sectors. The coefficient on $SiteVisit^{3day}$ for high-pollution industries is –0.024 when the dependent variable is abnormal pollution ($Pollution^{abn}$), and is significant at the 5% level. This estimate is nearly double the magnitude of the coefficient for low-pollution industries (–0.013). The difference between the coefficients is statistically significant (p-value = 0.070). We observe a similar pattern when using raw pollution (*Pollution*) as the outcome variable. This evidence suggests that strategic abatement is not a uniform practice but is concentrated in sectors where environmental risks are most material to investors.

[Insert Table 3 about here]

5.2. Firm valuation

Next, we explore how firm valuation influences the motivation for strategic pollution control. Firms with high valuations—often characterized by significant growth opportunities—typically rely more heavily on external financing and are more sensitive to investor sentiment (Baker & Wurgler, 2002). Consequently, the marginal benefit of influencing investor perceptions during a site visit should be higher for these firms. We use *Tobin's Q* as our proxy

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[5] Ministry of Ecology and Environment, "Classified Management Directory of Environmental Protection Verification for Listed Companies," https://www.mee.gov.cn/gkml/hbb/bgth/200910/t20091022_174891.htm.

for firm valuation, calculated as the ratio of the market value of equity plus the book value of liabilities to the book value of assets. We split the sample into "High *Tobin's Q*" and "Low *Tobin's Q*" groups based on the industry median and re-estimate the baseline model for each subsample.

The results are reported in Table 4. As expected, the strategic pollution reduction is driven entirely by high-valuation firms. When examining abnormal pollution ($Pollution^{abn}$), the coefficient for the high *Tobin's Q* subsample is –0.027 and significant at the 1% level, whereas the coefficient for low-valuation firms is virtually zero. The difference between these groups is statistically significant at the 1% level (p-value < 0.0000). A similar pattern is observed for the raw pollution measure (*Pollution*), where the high valuation group shows a significant reduction (–0.030) compared to a null result for the low valuation group. This finding implies that the pressure to maintain market confidence and support high valuations acts as a powerful catalyst for strategic behavior under the spotlight of external monitors.

[Insert Table 4 about here]

5.3. ESG performance

We further investigate how firms' strategic pollution reduction varies with their ESG performance. Incentives to manipulate pollution levels during site visits likely differ across the environmental, social, and governance dimensions. For the environmental (E) component, we predict that firms with poor records (low E ratings) will be more aggressive in cutting emissions. Analogous to firms in high-pollution industries, these entities face higher legitimacy risks and are under greater pressure to mask their poor baseline performance to mitigate regulatory penalties or investor backlash. The prediction for the social (S) component is less clear; while low social responsibility may correlate with higher societal costs for negative externalities, the direct link to immediate pollution control is less distinct than for environmental factors.

In contrast, for the governance (G) component, we predict that firms with strong governance (high G ratings) will exhibit stronger strategic responses. High governance implies strict internal controls and rigorous shareholder monitoring. Managers in these firms are subject to greater discipline and are acutely aware that allowing visitors to witness pollution could expose firms' weakness and damage the firms' valuation. Consequently, these managers are likely to be more "jittery" about upcoming visits and possess the managerial capacity to execute preemptive cleanups to protect their careers and shareholder value.

To test these predictions, we utilize the ESG ratings provided by the Sino-Securities Index, which scores firms on a scale of 1 to 9 for both composite and sub-scores, with a higher rating indicating better performance.[6] We classify firms as having a "High Rating" if their score is greater than 4, and a "Low Rating" if their score is equal to or less than 4. By decomposing the composite ESG score into its three specific components (E, S, and G), we can disentangle these competing mechanisms and better understand what drives the strategic behavior.

The analysis results are presented in Table 5. Panel A first presents the results for the composite scores. We find that the pollution reduction effect is statistically significant only among firms with low overall ESG ratings (–0.019 for $Pollution^{abn}$), whereas the estimate for high-ESG firms is statistically insignificant.

[Insert Table 5 about here]

Panels B-D reveal the nuances behind this aggregate result. In Panel B, consistent with our prediction regarding risk mitigation, the results are driven by firms with Low E ratings. This finding mirrors the results in Section 5.1: entities with the highest "baseline dirtiness" and liability risk are the most aggressive in cutting emissions. In Panel C, we observe that while firms with Low S ratings show a significant reduction in pollution, the difference between the Low and High S groups is not statistically significant. This suggests that the social dimension is less distinctive in driving this specific form of strategic behavior compared to environmental

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[6] ESG rating data are collected from the Sino-Securities Index Information Service (Shanghai) Co. Ltd. See https://www.chindices.com/bond-ratings.html.

and governance factors.

Crucially, Panel D shows that firms with High G ratings exhibit significantly stronger responsiveness than their Low G counterparts. This aligns with the “jittery manager” hypothesis and the findings in Section 5.2 regarding firm valuation. Just as high-Tobin's Q firms have the market incentive to manage perceptions, high-governance firms possess the managerial capacity and disciplinary incentives to execute these strategic interventions effectively.

To verify this governance channel, we conduct an additional test using conventional measures of internal and external governance. We gauge internal governance using managerial compensation (*ExePay*), defined as the logarithm of one plus the total compensation of the top three executives. We gauge external governance using institutional ownership (*IO*), calculated as the number of shares held by institutional investors divided by the total number of shares outstanding. Low executive compensation or high institutional ownership indicate lower management entrenchment and stronger governance (Core *et al.*, 1999; Appel *et al.*, 2016; Wang *et al.*, 2025).

As reported in Table 6, the results corroborate our governance findings: the strategic reduction in pollution is driven by firms with stronger governance structures. Regarding internal governance (Panel A), the coefficient on $SiteVisit^{3day}$ is negative and statistically significant for the Low *ExePay* subsample (–0.019), whereas it is insignificant for the High *ExePay* subsample (–0.011). Similarly, for external governance (Panel B), the effect is concentrated in the High *IO* subsample, which exhibits a significant coefficient of –0.019, compared to a small and insignificant coefficient (–0.008) for the Low *IO* group. The difference between the subsamples are statistically significant.

Collectively, these findings imply a dual mechanism: the *necessity* to reduce pollution is driven by environmental liability (Low E), while the *ability* and *discipline* to do so are facilitated by strong governance (High G).

[Insert Table 6 about here]

5.4. Visitor ownership stake and PRI signatory

The results thus far indicate that firms' strategic behaviors are driven by environmental risk, valuation, and governance. However, a key question remains: how do these factors transmit to specific firm behaviors? One possibility is a *reputation* channel, whereby firms are sensitive to scrutiny from environmentally conscious visitors who may expose pollution to more audience, thereby increasing regulatory risk or the cost of capital. A second possibility is an *ownership* channel, where firms respond to visitors holding significant equity stakes. Upon observing pollution, these investors may sell their shares, either due to concerns over regulatory risk or to comply with ESG investment mandates.

To distinguish between these mechanisms, we investigate whether the observed pollution reduction is driven by visitors with an ownership stake or by signatories to the PRI.[7] If the cleanup is primarily motivated by the reputation channel, we would expect PRI signatories to elicit a significant response. Conversely, if the ownership channel is the ultimate driver, strategic pollution reduction should be concentrated among visitors with existing equity stakes only.

To systematically identify these visitor types, we construct specific measures for shareholder status and PRI signatory status. We leverage the mandatory disclosure of top ten shareholders under securities regulations and obtain the data from the CSMAR dataset. We match these shareholder names to visitor information using a fuzzy matching algorithm.[8] Based on these matches, we define *Stake* as a binary indicator equal to one if the visiting group

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[7] PRI is a United Nations-supported international network of investors working to understand the investment implications of environmental, social, and governance (ESG) factors. Signatories commit to six aspirational principles that encourage incorporating ESG issues into investment analysis and decision-making processes (see https://www.unpri.org/).

[8] We employ the rapidfuzz package with a 70% similarity threshold to account for data inconsistencies, such as abbreviations or typographical errors (see https://pypi.org/project/RapidFuzz/).

includes at least one shareholder, and *nonStake* as one if it does not. We also construct continuous variables, *Stake_Num* and *nonStake_Num*, to capture the number of shareholders and non-shareholders involved in each visit, respectively. To capture the presence of environmentally conscious investors, we obtain the list of institutional PRI signatories from the United Nations PRI. We employ the same fuzzy matching algorithm to link PRI signatories with the visitor records. We define *PRI* as an indicator equal to one if the visiting group includes a PRI signatory, and *nonPRI* as one if it does not. Similarly, *PRI_Num* and *nonPRI_Num* measure the respective counts of PRI signatories and non-signatories. To conduct the test, we modify the baseline equation by substituting the single *SiteVisit* variable with the corresponding pair of mutually exclusive visitor indicators (e.g., *Stake* and *nonStake*) or their count equivalents.

[Insert Table 7 about here]

We first test the ownership channel by distinguishing between visits from shareholders and non-shareholders. The results are shown in Panel A of Table 7. The estimates indicate that the strategic reduction in pollution is concentrated during visits by existing shareholders. The coefficient for *Stake* visitors is negative and statistically significant at the 5% level (−0.040) when the dependent variable is abnormal pollution ($Pollution^{abn}$). In contrast, the coefficient for non-stakeholders (*nonStake*) is smaller in magnitude (−0.010) and statistically indistinguishable from zero. The difference between these two groups is statistically significant (p-value = 0.080). When using visitor counts, the pattern persists: the coefficient for *Stake_Num* is significantly negative, whereas the coefficient for *nonStake_Num* shows no such effect. We observe qualitatively similar results when using raw pollution (*Pollution*) as the outcome variable. These findings suggest that managers perceive a higher cost of revealing "dirty" operations to visitors who hold voting power and cash flow rights.

Next, we test the reputation channel by investigating whether the "green" label of visitors—specifically their status as PRI signatories—induces firms to strategically reduce pollution. Panel B shows no evidence that PRI signatories elicit a stronger pollution reduction response than non-signatories. The coefficient for *PRI* visitors is statistically insignificant when examining abnormal pollution ($Pollution^{abn}$), while the coefficient for *nonPRI* visitors is negative and marginally significant. Crucially, the difference between the two coefficients is statistically insignificant (p-value = 0.704), indicating that a visitor's status as a responsible investor does not, in isolation, trigger a differential strategic response from the firm. Similar patterns are observed for the raw pollution outcome (*Pollution*).

Finally, we conduct a "horse race" analysis between the two effects in Panel C. This specification includes both the *Stake* and *PRI* indicators (and their count equivalents) simultaneously. When both factors are controlled for, the dominance of the ownership channel becomes even more pronounced. In the specifications of $Pollution^{abn}$, the coefficient on *Stake* increases in magnitude to −0.046 and remains significant at the 5% level, whereas the coefficient on *PRI* turns positive and insignificant. The difference between the shareholder and non-shareholder coefficients remains notable (p-value = 0.074). The pattern is similar in the specifications of *Pollution*. Collectively, these results imply that the "unwatched pollution" phenomenon is primarily a response to the monitoring power derived from ownership rather than the stated environmental preferences of the visitors. Managers appear to strategically clean up for those who own the firm, regardless of whether those owners have explicitly pledged to uphold ESG principles.

In conclusion, these findings elucidate the underlying mechanism: The strategic reduction of pollution is not primarily driven by a reputation channel associated with environmentally conscious visitors. Instead, it appears to be an ownership-driven response. Managers in pollution-intensive or environmentally poor-performing firms (Sections 5.1 and 5.3) who oversee high-valuation assets (Section 5.2) and operate under strict governance regimes

(Section 5.3) are acutely sensitive to the scrutiny of major shareholders (Section 5.4). This sensitivity leads them to temporarily sanitize operations, a tactic designed to protect the firm's market value and their own professional standing rather than to achieve genuine environmental sustainability.

6. Additional analysis

We conduct additional analysis to validate our findings, exclude alternative explanations, and explore the channels of pollution reduction.

6.1. The effect of online visits

To further validate that the observed pollution reduction is driven by the physical presence of external monitors, we employ online site visits as a placebo test. Unlike physical visits, online interactions (such as teleconferences or web-based Q&A sessions) do not involve direct observation of production facilities and thus should not trigger the same immediate “cleanup” incentives. If our argument regarding physical monitoring is correct, we should observe significant pollution abatement only during physical site visits, but not during online interactions.

Figure IA1 presents the dynamic coefficients for online visits, estimated using the same specification as our baseline dynamic model. Consistent with our hypothesis, and in sharp contrast to the distinct “V-shaped” reduction observed during physical visits, the coefficients for online visits are statistically indistinguishable from zero throughout the entire event window. This null result confirms that the “unwatched pollution” phenomenon is uniquely tied to the physical presence of external monitors.

6.2. The effect on sister non-visited sites

A potential concern with our identification strategy is that the observed pollution reduction might be driven by unobserved firm-level factors, such as a company-wide initiative to improve ESG performance or other simultaneous shocks affecting the entire organization. To address this, we conduct a placebo test by comparing the pollution dynamics of visited sites to those of non-visited sites within the same firm. If our hypothesis regarding physical monitoring is correct, the strategic abatement should be strictly localized to the specific facility hosting the visitors. Non-visited sites, lacking the immediate pressure of external scrutiny, should not exhibit similar pollution reductions.

To implement this test, we construct two indicators for non-visited sites belonging to the same firm as the visited site. We define *SameCity* as an indicator equal to one for non-visited sister sites located in the same city as the visited facility. This variable is particularly useful for ruling out coordinated regional responses or city-specific shocks that might affect multiple facilities of the same firm simultaneously. We define *DiffCity* as an indicator equal to one for non-visited sister sites located in different cities. This variable allows us to test for firm-wide policy changes or aggregate shocks that might prompt simultaneous abatement across all production units, regardless of their geographic location.

Table 8 reports the results of this analysis. Panel A presents the estimates for *SameCity* (and its three-day window equivalent, $SameCity^{3day}$), while Panel B presents the estimates for *DiffCity* (and its three-day window equivalent, $DiffCity^{3day}$). Across all specifications, the coefficients on these placebo visit indicators are small in magnitude and statistically insignificant. For instance, the coefficient on $SameCity^{3day}$ in the abnormal pollution specification is 0.005 (p-value > 0.10), indicating no detectable change in pollution at sister sites, even when they are geographically close to the visited location. Similarly, sites in different regions show no significant response. These null results reinforce the conclusion that the pollution reduction is not a general firm-level phenomenon but is uniquely triggered by the physical presence of monitors at the specific site.

[Insert Table 8 about here]

6.3. Channels of pollution reduction: Production suspension versus abatement efforts

Finally, we address the question of *how* firms achieve the observed reduction in pollution. A reduction in emissions could result from either a temporary suspension of production activities or the strategic deployment of pollution control technologies (e.g., turning on scrubbers or filters that are otherwise left idle). Distinguishing between these effects is crucial for understanding the channel of "greenwashing." If firms merely halt production, the pollution drop is a mechanical byproduct of inactivity. However, if production remains constant while pollution falls, it points to the strategic use of abatement technology to mask true emission intensities.

To test the production suspension hypothesis, we utilize satellite-derived TIR data as a proxy for real-time industrial activity, following the methodology of Xue *et al.* (2025). Manufacturing processes generate significant heat, making TIR an effective measure of operating intensity that is distinct from pollution output. We define *TIR* as the average daytime thermal infrared radiation value (measured in Kelvin) in the plant area of the specific site on day *t*. To account for local thermal variations, we also construct an abnormal measure, *AR*, defined as the difference between the site's *TIR* and the average *TIR* of a surrounding 5km buffer zone on day *t*.

We estimate the impact of site visits on these operational proxies using a specification analogous to our baseline model. Specifically, we regress *TIR* and *AR* on our visit indicators (*SiteVisit* or $SiteVisit^{3day}$), controlling for the site's physical area size (*SiteAreaSize*), lagged operational activity (i.e., *TIR* or *AR* calculated over the [t-14, t-7] window), as well as site and city-date fixed effects. Table 9 presents the results[9]. The coefficients on *SiteVisit* and $SiteVisit^{3day}$ are statistically insignificant across all specifications, indicating that site visits do not trigger a significant reduction in operational heat signatures. These null results imply that

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[9] The number of observations in this analysis is smaller because TIR measurements are frequently unavailable due to cloud cover and other weather-condition constraints.

firms do not achieve cleaner air by shutting down factories, as such inactivity might signal operational weakness to investors.

[Insert Table 9 about here]

Instead, the evidence points to the strategic deployment of abatement technologies. To test this channel, we examine whether the pollution reduction is conditional on the firm's existing capacity to treat emissions. If firms decouple emissions from output by ramping up end-of-pipe treatments, the effect should be more pronounced for firms equipped with such facilities. We proxy for installed abatement capacity (*IAC*) using the frequency of pollution-control keywords (e.g., “desulfurization,” “denitrification,” “dust collector,” “environmental protection equipment,” and “pollution control equipment”) in the firm's annual report Management Discussion and Analysis (MD&A) released before the visit events. We define firms as having “High *IAC*” if they mention any of these keywords in their MD&A, and “Low *IAC*” if they do not.

Table 10 reports the results of this analysis. We find that the strategic reduction in pollution is significantly stronger for firms with High *IAC*. Specifically, for the abnormal pollution measure ($Pollution^{abn}$), the coefficient for High *IAC* firms is -0.039 (significant at the 5% level), nearly four times the magnitude of the coefficient for Low *IAC* firms (-0.010). The difference between these groups is statistically significant at the 1% level (p-value < 0.000). A similar pattern holds for raw pollution levels (*Pollution*).

Collectively, these findings suggest a sophisticated form of strategic compliance. Firms do not disrupt economic production to please visitors; instead, they leverage their installed environmental infrastructure to temporarily sanitize visible emissions. This behavior allows managers to present a “clean” image without sacrificing output, effectively decoupling environmental performance from economic activity during periods of scrutiny.

[Insert Table 10 about here]

7. Conclusion

This study provides the first firm-level evidence that corporate site visits—a key channel for information acquisition—induce strategic changes in real environmental behavior. We document that manufacturing firms temporarily suppress pollution emissions when investors are present, creating a favorable but transient "green" impression. The effects are most pronounced among firms in heavy-polluting industries, where environmental risks are salient, as well as among firms with high market valuations and strong governance. Furthermore, we find that the effect is driven by visits from existing shareholders rather than by the environmental mandates of visitors (e.g., PRI signatories). This suggests that managers clean up to protect firm value and their own standing before owners, rather than to signal social responsibility.

Mechanistically, we find that firms do not suspend production but instead rely on established pollution control infrastructure to curb emissions. This suggests managers strategically deploy abatement technologies to decouple environmental performance from operational output without disrupting economic activity.

Overall, we document the strategic manipulation of pollution emissions during investor site visits, identifying a novel form of corporate real activity management. These findings suggest that seeing may not be believing, underscoring the necessity of complementing on-site diligence with continuous, independent environmental monitoring.

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Appendix 1: Variable definitions and data sources

Variable	Definition	Source
Outcome variables:		
Pollution	The average PM2.5 concentration ($\mu g/m^3$) within a 1km radius of the specific site on day *t*.	CHAP Database
$Pollution^{ring}$	The average PM2.5 concentration ($\mu g/m^3$) within a buffer ring of 1km to 3km radius surrounding the site on day *t*.	CHAP Database
$Pollution^{abn}$	The difference between the site-specific pollution and the surrounding environmental pollution ($Pollution$ - $Pollution^{ring}$) on day *t*.	CHAP Database
$Pollution^{lag}$	The average level of *Pollution* calculated over the pre-event window [*t-14*, *t-7*].	CHAP Database
TIR	The average daytime thermal infrared radiation value (*Kelvin*) at the site on day *t*, used as a proxy for operational activity.	Xue et al. (2025)
AR	The difference between the site's daytime *TIR* and the average *TIR* (*Kelvin*) of a 5km buffer zone surrounding the site on day *t*.	Xue et al. (2025)
Key independent variables:		
SiteVisit	1 if the site receives a corporate visit on day *t*, and 0 otherwise.	CSMAR
$SiteVisit^{3day}$	1 if the site receives a corporate visit on days *t* -1, *t*, or *t* + 1, and 0 otherwise.	CSMAR
Visitor type indicators: All visitor types below are defined as dummy variables equal to 1 if the visiting group includes at least one representative from the specified sector, and 0 otherwise.		
Advisor	1 if the visitors include participants from an investment advisory company, and 0 otherwise.	CSMAR
Assman	1 if the visitors include participants from an assets management company, and 0 otherwise.	CSMAR
Bank	1 if the visitors include participants from the banking sector, and 0 otherwise.	CSMAR
Foreign	1 if the visitors include participants from a foreign institution (QFII/RQFII), and 0 otherwise.	CSMAR
Funds	1 if the visitors include participants from a mutual fund or private equity fund, and 0 otherwise.	CSMAR
Futures	1 if the visitors include participants from a futures company, and 0 otherwise.	CSMAR
Individual	1 if the visitors include individual investors, and 0 otherwise.	CSMAR
Insurance	1 if the visitors include participants from an insurance company, and 0 otherwise.	CSMAR
Media	1 if the visitors include participants from a media organization, and 0 otherwise.	CSMAR

Securities	1 if the visitors include participants from a securities firm (investment bank/brokerage), and 0 otherwise.	CSMAR
Others	1 if the visitors include participants who do not fall into the above categories, and 0 otherwise.	CSMAR
Other visit characteristics:		
Ln(# Word)	The natural logarithm of the total word count of the disclosure record filed for the specific site visit event.	CSMAR
Ln(# Institution)	The natural logarithm of the count of distinct visiting institutions participating in the site visit event.	CSMAR
Ln(# Researcher)	The natural logarithm of the count of distinct individuals participating in the site visit event.	CSMAR
Online	1 if the visit was conducted virtually (e.g., teleconference, webinar) rather than physically, and 0 otherwise.	CSMAR
Stake	1 if the visiting group includes a shareholder in the site visit on a day, and 0 otherwise.	CSMAR
nonStake	1 if the visiting group does not include a shareholder in the site visit on a day, and 0 otherwise.	CSMAR
Stake_Num	The number of visitors who are the shareholders of the firm in the site visit on a day, and 0 otherwise.	CSMAR
nonStake_Num	The number of visitors who are not the shareholders of the firm in the site visit on a day, and 0 otherwise.	CSMAR
PRI	1 if the visiting group includes a PRI signatory in the site visit on a day, and 0 otherwise.	https://www.unpri.org/ & CSMAR
nonPRI	1 if the visiting group does not include a PRI signatory in the site visit on a day, and 1 otherwise.	https://www.unpri.org/ & CSMAR
PRI_Num	The number of visitors who are signatories to the PRI in the site visit on a day, and 0 otherwise.	https://www.unpri.org/ & CSMAR
nonPRI_Num	The number of visitors who are signatories to the PRI in the site visit on a day, and 0 otherwise.	https://www.unpri.org/ & CSMAR
SameCity	1 for non-visited sites belonging to the same firm and located in the same city as the visited site on the event date, and 0 otherwise.	CSMAR
DiffCity	1 for non-visited sites belonging to the same firm but located in a different city than the visited site on the event date, and 0 otherwise.	CSMAR
Other variables:		

ESG Rating	Composite ESG rating provided by Sino-Securities Index.	WIND Database
E/S/G Rating	Individual Environmental (E), Social (S), and Governance (G) sub-ratings provided by the Sino-Securities Index.	WIND Database
HighPollution	1 if the firm operates in a heavily polluting industry (e.g., thermal power, steel, cement, chemicals), and 0 otherwise.	CSMAR
Tobin's Q	The ratio of market value of equity plus book value of liabilities to the book value of assets.	CSMAR
ExePay	Logarithm value of 1 plus total compensation of the top three executives.	CSMAR
IO	The number of shares held by institutional investors over the number of total shares outstanding.	CSMAR
SiteAreaSize	The area size (m^2) of the plant site.	Xue et al. (2025)
IAC	The intensity of pollution-abatement discussion in a firm's annual report MD&A, measured using the frequency of keywords "desulfurization," "denitrification," "dust collector", "environmental protection equipment", and "pollution control equipment".	CSMAR

Note: For all variables denoting a specific visitor type (e.g., *Bank*, *Funds*, *Media*) or location characteristic (e.g., *SameCity* and *DiffCity*), we also construct a corresponding 3-day window variable (superscripted with *3day*). These variables are equal to 1 if the respective indicator is active on day *t*-1, *t*, or *t*+1, and 0 otherwise.

Appendix 2: The distribution of visits by visitor type

Type	Number	Percentage
Total number of site visits (*SiteVisit*)	30,948	100.00
Visits by type:		
- Securities firm (*Securities*)	24,769	80.03
- *Funds*	19,068	61.61
- Assets management companies (*Assman*)	12,909	41.71
- Foreign institutions (*Foreign*)	4,427	14.30
- Insurance companies (*Insurance*)	2,815	9.10
- Individuals (*Individual*)	972	3.14
- Banks (*Bank*)	815	2.63
- Investment advisor companies (*Advisor*)	617	1.99
- *Media*	571	1.85
- *Others*	401	1.30
- Futures companies (*Futures*)	162	0.52

Notes: This table summarizes the frequency and percentage distribution of corporate site visits across different visitor categories for the full sample of 30,948 visit events.

Appendix 3: The impact of site visits on local air pollution by visitor type

Panel A: Visitors from investment advisor companies

	(1)	(2)	(3)	(4)
Dependent variable	$Pollution^{abn}$		$Pollution$	
$Advisor$	-0.047		-0.042	
	(0.047)		(0.050)	
$Advisor^{3day}$		-0.032		-0.026
		(0.030)		(0.033)

Panel B: Visitors from asset management companies

	(1)	(2)	(3)	(4)
Dependent variable	$Pollution^{abn}$		$Pollution$	
$Assman$	-0.027**		-0.024**	
	(0.011)		(0.011)	
$Assman^{3day}$		-0.021***		-0.020**
		(0.007)		(0.008)

Panel C: Visitors from banks

	(1)	(2)	(3)	(4)
Dependent variable	$Pollution^{abn}$		$Pollution$	
$Bank$	-0.062		-0.062	
	(0.039)		(0.040)	
$Bank^{3day}$		-0.026		-0.029
		(0.027)		(0.030)

Panel D: Foreign visitors

	(1)	(2)	(3)	(4)
Dependent variable	$Pollution^{abn}$		$Pollution$	
$Foreign$	-0.008		0.000	
	(0.017)		(0.019)	
$Foreign^{3day}$		-0.010		-0.006
		(0.012)		(0.013)

Panel E: Visitors from futures companies

	(1)	(2)	(3)	(4)
Dependent variable	$Pollution^{abn}$		$Pollution$	
$Futures$	-0.010		0.007	
	(0.088)		(0.103)	
$Futures^{3day}$		0.020		0.036
		(0.051)		(0.055)

Panel F: Visitors from funds companies

	(1)	(2)	(3)	(4)
Dependent variable	$Pollution^{abn}$		$Pollution$	
$Funds$	-0.017*		-0.016	
	(0.009)		(0.010)	
$Funds^{3day}$		-0.015**		-0.014*
		(0.007)		(0.007)

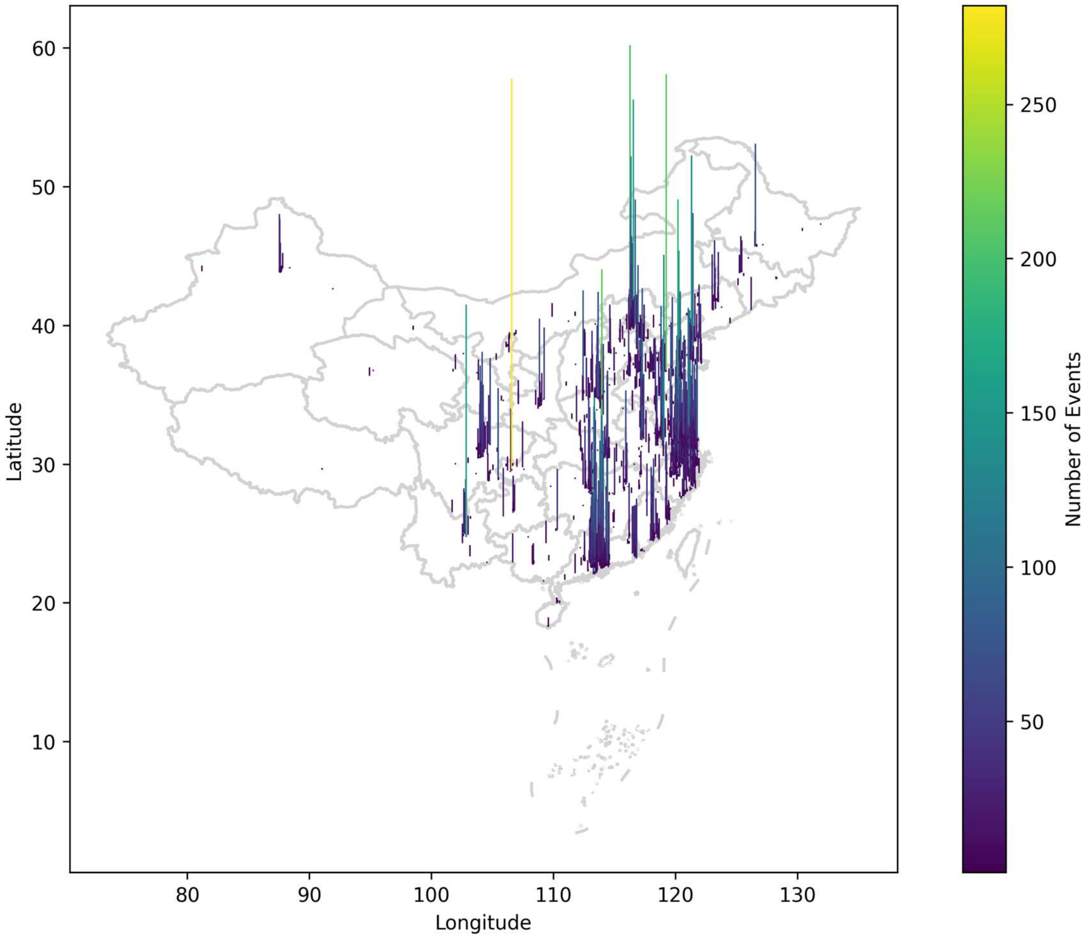
Panel G: Individual visitors

	(1)	(2)	(3)	(4)
Dependent variable	$Pollution^{abn}$		$Pollution$	
$Individual$	-0.044		-0.033	
	(0.040)		(0.042)	
$Individual^{3day}$		-0.040		-0.032
		(0.028)		(0.031)

Panel H: Visitors from insurance sector				
	(1)	(2)	(3)	(4)
Dependent variable	*Pollution*^{abn}		*Pollution*	
Insurance	-0.004		0.003	
	(0.021)		(0.023)	
Insurance^{3day}		-0.008		-0.006
		(0.015)		(0.016)
Panel I: Visitors from media sector				
	(1)	(2)	(3)	(4)
Dependent variable	*Pollution*^{abn}		*Pollution*	
Media	-0.036		-0.040	
	(0.049)		(0.053)	
Media^{3day}		0.004		0.006
		(0.034)		(0.036)
Panel J: Visitors from securities companies				
	(1)	(2)	(3)	(4)
Dependent variable	*Pollution*^{abn}		*Pollution*	
Securities	-0.014*		-0.015*	
	(0.008)		(0.008)	
Securities^{3day}		-0.014**		-0.015**
		(0.006)		(0.006)
Panel K: Others				
	(1)	(2)	(3)	(4)
Dependent variable	*Pollution*^{abn}		*Pollution*	
Others	0.028		0.029	
	(0.055)		(0.056)	
Others^{3day}		0.040		0.034
		(0.038)		(0.039)
N	6,908,720	6,908,720	6,908,720	6,908,720
Controls	Yes	Yes	Yes	Yes
Site FE	Yes	Yes	Yes	Yes
City-date FE	Yes	Yes	Yes	Yes

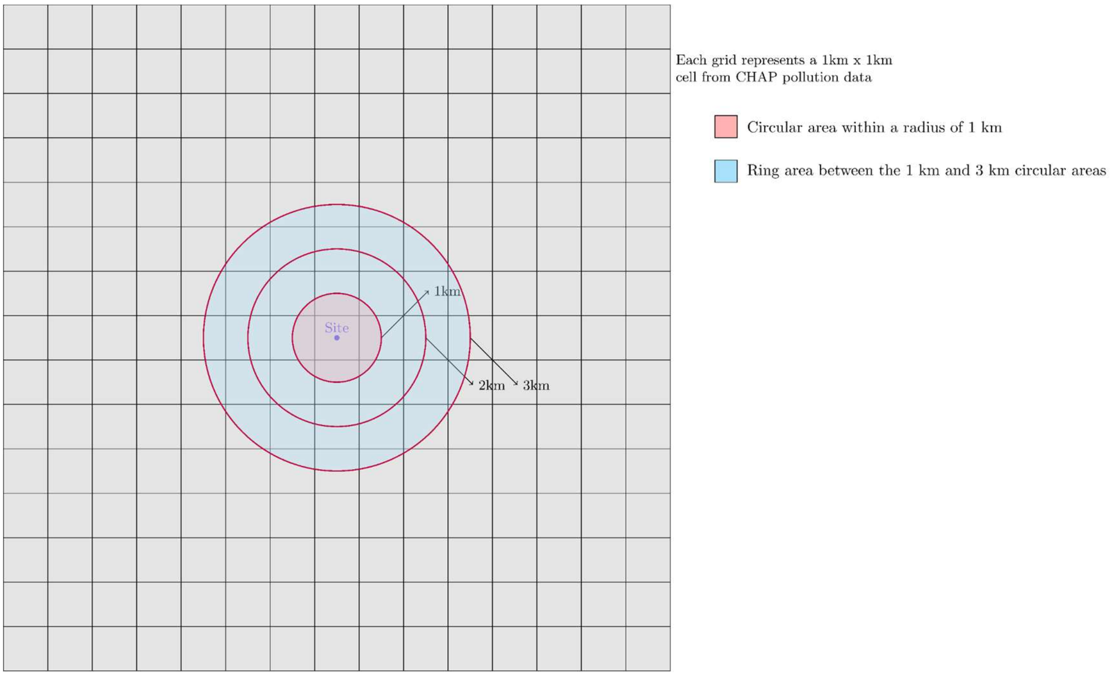
Notes: This table presents regression estimates of the effects of corporate site visits on local air pollution, stratified by the type of visiting institution. The dependent variable in columns (1) and (2) is *Pollution*^{abn}, defined as the difference between the average PM2.5 concentration within a 1km radius of the site (*Pollution*) and the average concentration within a surrounding 1km to 3km buffer ring (*Pollution*^{ring}). In columns (3) and (4), the dependent variable is the raw pollution level (*Pollution*). The analysis is organized into eleven panels (A through K), each corresponding to a specific category of visitor: investment advisor companies, asset management companies, banks, foreign visitors, futures companies, funds companies, individual visitors, the insurance sector, the media sector, securities companies, and others. The primary independent variables are the specific visitor-type indicators for the visit day and the three-day window surrounding the visit. All models include controls for concurrent surrounding pollution (*Pollution*^{ring}) and lagged pollution (*Pollution*^{lag}), calculated as the average pollution level over the pre-event window [*t*-14, *t*-7], alongside site and city-date fixed effects. All variables are defined in Appendix 1. Standard errors are clustered at the site level and are shown in parentheses, with *, **, and *** denoting statistical significance at the 10%, 5%, and 1% levels, respectively.

Figure 1: Geographic distribution of sites and frequency of visits across China



Note: This figure displays the geographic distribution of sampled sites across China. Vertical bars mark specific site locations, with both the height and color of the bars representing the number of visits or events that occurred at that specific site.

Figure 2: The constructure of site pollution



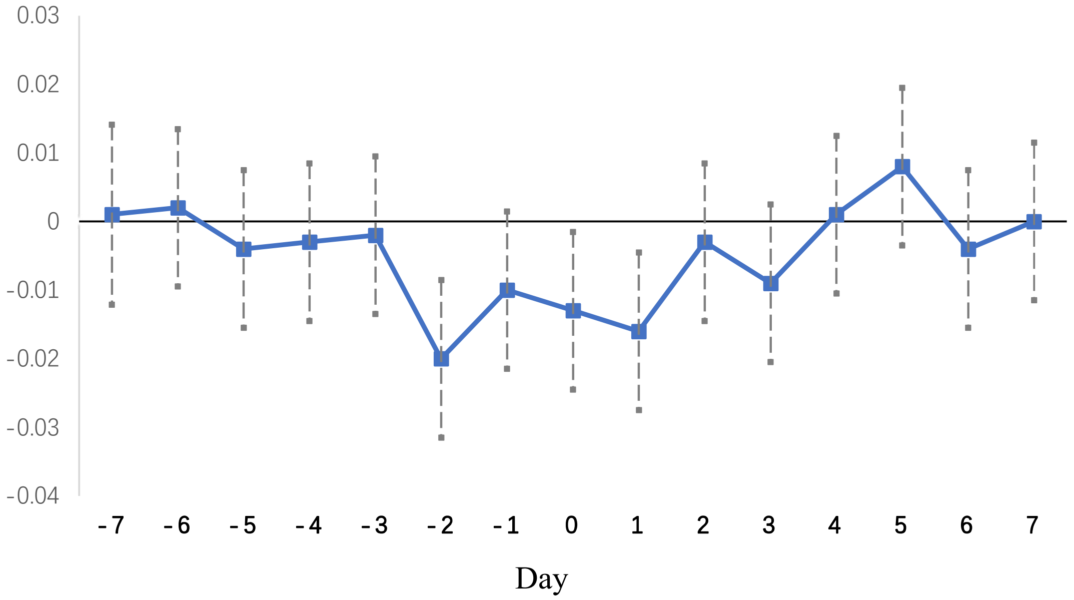
Pollution: The average PM2.5 concentration (*μg/m*^{3}) within a 1km radius of the specific site on a day.

Pollution^{ring}: The average PM2.5 concentration (*μg/m*^{3}) within a buffer ring of 1km to 3km radius surrounding the site on a day.

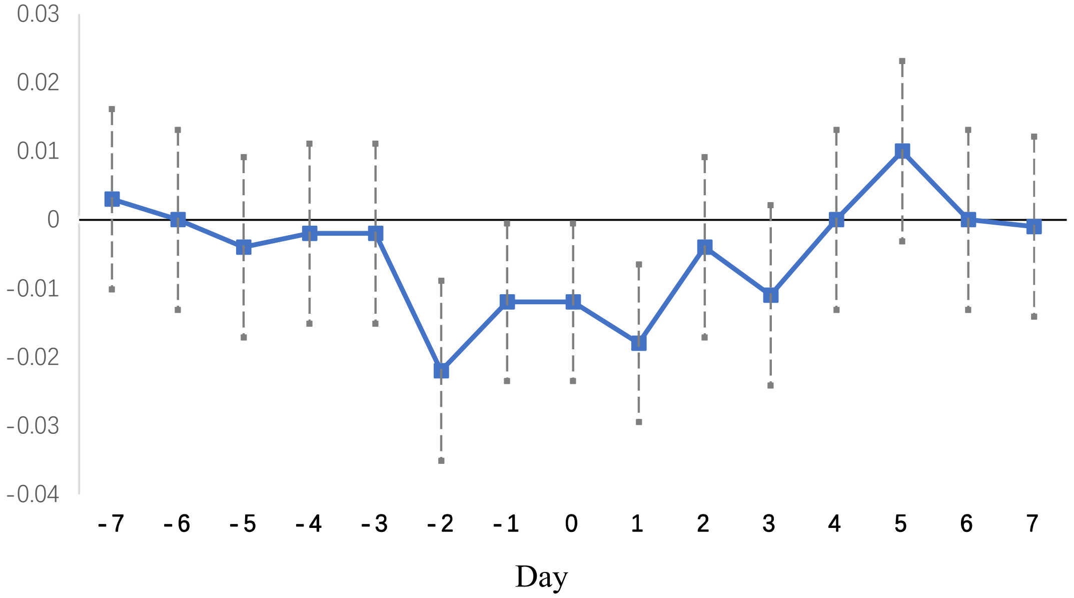
Pollution^{abn}: The difference between the site-specific pollution and the surrounding environmental pollution (*Pollution* - *Pollution*^{ring}) on a day.

Figure 3: Dynamic impacts of site visits on local air pollution over a 14-day window

Panel A: Abnormal pollution, $Pollution^{abn}$



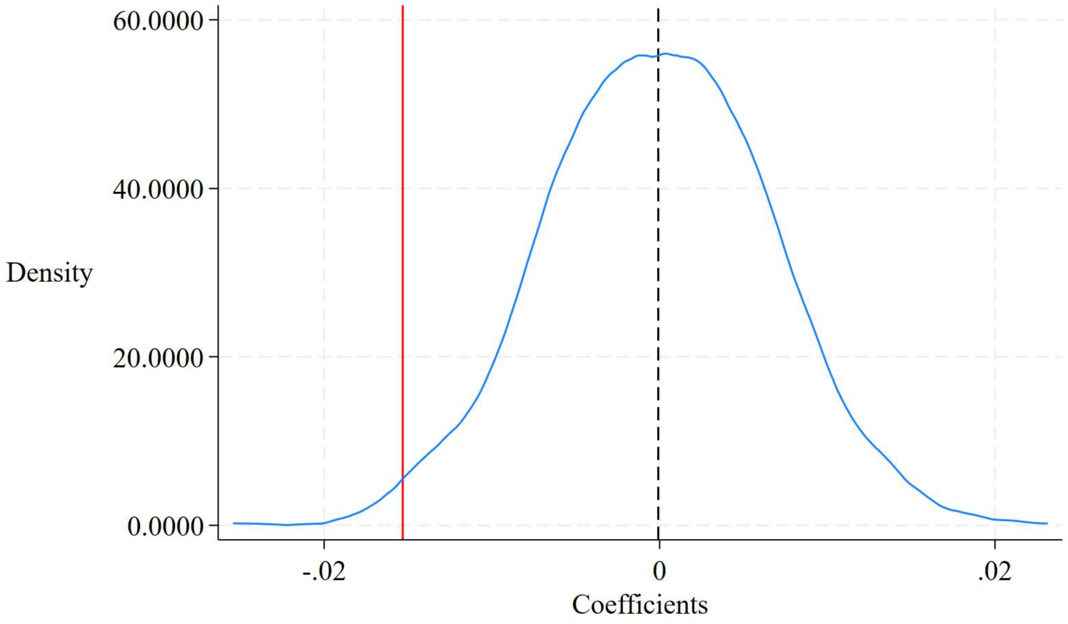
Panel B: Average pollution, *Pollution*



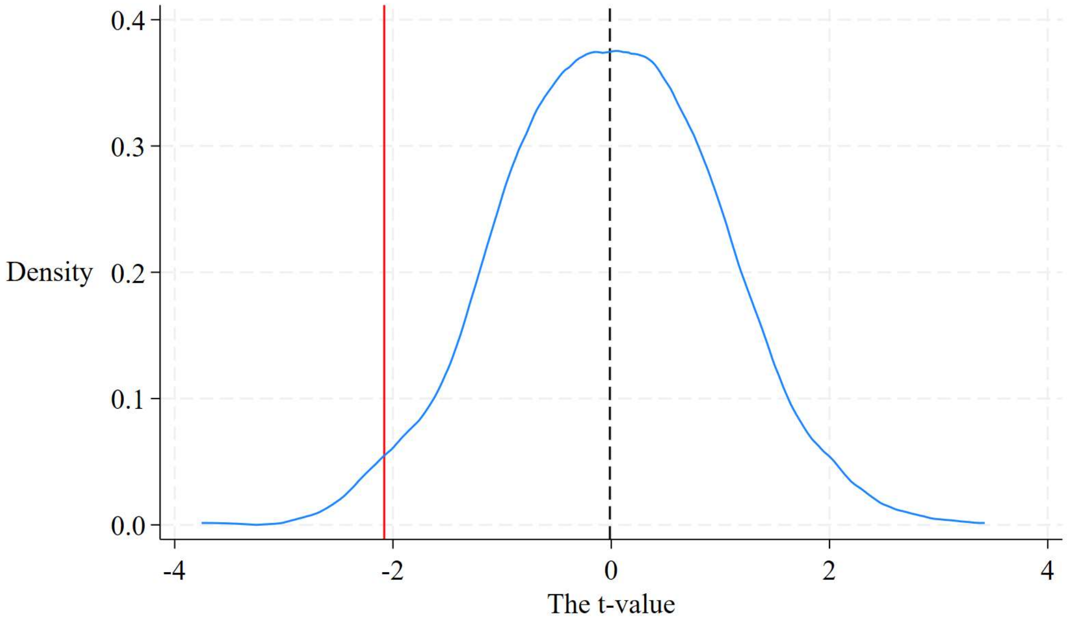
Notes: This figure illustrates the dynamic effects of corporate site visits on local air pollution across a 14-day window surrounding the visit event. The analysis plots the estimated coefficients and corresponding confidence intervals (90% level) for a series of dummy variables representing specific days relative to the site visit, ranging from 7 days before (t-7) to 7 days after (t+7) the event. Panel A displays the results for abnormal pollution ($Pollution^{abn}$), while Panel B shows the results for average pollution (*Pollution*). The horizontal axis represents the timeline relative to the visit day (Day 0), and the vertical axis indicates the magnitude of the estimated impact on pollution levels.

Figure 4: Falsification tests

Panel A: Plot of coefficients



Panel B: Plot of t-value



Notes: This figure presents the results of a placebo test using a randomization procedure to validate the baseline findings. The analysis involves 1,000 simulations where the *SiteVisit* variable is randomly assigned to observations, after which the baseline regression model is re-estimated. Panel A displays the kernel density plot of the estimated coefficients from these 1,000 placebo regressions, with the vertical red line indicating the actual coefficient estimate from the baseline model and the dashed line marking zero. Panel B shows the kernel density plot of the corresponding *t*-values, with the vertical red line representing the actual *t*-value from the baseline model and the dashed line marking zero.

Table 1: The impact of site visits on local air pollution

	(1)	(2)	(3)	(4)
Dependent variable	$Pollution^{abn}$		$Pollution$	
$SiteVisit$	-0.015**		-0.015*	
	(0.007)		(0.008)	
$SiteVisit^{3day}$		-0.016***		-0.017***
		(0.006)		(0.006)
$Pollution^{ring}$	0.026***	0.026***	1.030***	1.030***
	(0.001)	(0.001)	(0.002)	(0.002)
$Pollution^{lag}$	0.011***	0.011***	0.013***	0.013***
	(0.001)	(0.001)	(0.002)	(0.002)
Site FE	Yes	Yes	Yes	Yes
City-date FE	Yes	Yes	Yes	Yes
N	6,908,720	6,908,720	6,908,720	6,908,720
Adj. R-sq	0.156	0.156	0.957	0.957

Notes: This table presents the regression estimates of the effect of corporate site visits on air pollution surrounding firm sites, using a sample of daily observations at the site level from January 1, 2012, to December 31, 2019. The dependent variable in columns (1) and (2) is $Pollution^{abn}$, defined as the difference between the average PM2.5 concentration within a 1km radius of the site (*Pollution*) and the average concentration within a surrounding 1km to 3km buffer ring ($Pollution^{ring}$). In columns (3) and (4), the dependent variable is the raw pollution level (*Pollution*). The primary independent variables are *SiteVisit*, an indicator equal to one if the site was visited on day *t*, and $SiteVisit^{3day}$, an indicator equal to one if a visit occurred on day *t*-1, *t*, or *t*+1. All models include controls for concurrent surrounding pollution ($Pollution^{ring}$) and lagged pollution ($Pollution^{lag}$), calculated as the average pollution level over the pre-event window [*t*-14, *t*-7], alongside site and city-date fixed effects. All variables are defined in Appendix 1. Standard errors are clustered at the site level and are shown in parentheses, with *, **, and *** denoting statistical significance at the 10%, 5%, and 1% levels, respectively.

Table 2: The impact of site visit intensity on local air pollution

Dependent variable	(1) $Pollution^{abn}$	(2) *Pollution*	(3) $Pollution^{abn}$	(4) *Pollution*	(5) $Pollution^{abn}$	(6) *Pollution*
Ln(# Word)	-0.002**	-0.002*				
	(0.001)	(0.001)				
Ln(# Researcher)			-0.008**	-0.007*		
			(0.004)	(0.004)		
Ln(# Institution)					-0.007*	-0.007
					(0.004)	(0.004)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Site FE	Yes	Yes	Yes	Yes	Yes	Yes
City-date FE	Yes	Yes	Yes	Yes	Yes	Yes
N	6,908,720	6,908,720	6,908,720	6,908,720	6,908,720	6,908,720
Adj. R-sq	0.156	0.957	0.156	0.957	0.156	0.957

Notes: This table presents regression estimates of the effect of corporate site visit intensity on air pollution surrounding firm sites, using a sample of daily observations at the site level from January 1, 2012, to December 31, 2019. The dependent variable in columns (1), (3), and (5) is $Pollution^{abn}$, defined as the difference between the average PM2.5 concentration within a 1km radius of the site (*Pollution*) and the average concentration within a surrounding 1km to 3km buffer ring ($Pollution^{ring}$). In columns (2), (4), and (6), the dependent variable is the raw pollution level (*Pollution*). The primary independent variables measure visit intensity: *Ln(# Word)* (columns 1 and 2) is the natural logarithm of the total word count of the visit disclosure record; *Ln(# Researcher)* (columns 3 and 4) is the natural logarithm of the count of visitors; and *Ln(# Institution)* (columns 5 and 6) is the natural logarithm of the count of visiting organizations. These variables take a value of zero if no visit occurred. All models include controls for concurrent surrounding pollution ($Pollution^{ring}$) and lagged pollution ($Pollution^{lag}$), calculated as the average pollution level over the pre-event window [*t*-14, *t*-7], alongside site and city-date fixed effects. All variables are defined in Appendix 1. Standard errors are clustered at the site level and are shown in parentheses, with *, **, and *** denoting statistical significance at the 10%, 5%, and 1% levels, respectively.

Table 3: The heterogeneous effects of site visits by industry pollution levels

	(1)	(2)	(3)	(4)
Dependent variable	$Pollution^{abn}$		$Pollution$	
Subsample	Low-pollution industries	High-pollution industries	Low-pollution industries	High-pollution industries
$SiteVisit^{3day}$	-0.013*	-0.024**	-0.013*	-0.028**
	(0.007)	(0.011)	(0.007)	(0.013)
Difference between the coefficients of $SiteVisit^{3day}$	(2)-(1): -0.011		(4)-(3): -0.015	
	P-value: 0.070		P-value: 0.020	
Controls	Yes	Yes	Yes	Yes
Site FE	Yes	Yes	Yes	Yes
City-date FE	Yes	Yes	Yes	Yes
N	4,715,800	2,192,920	4,715,800	2,192,920
Adj. R-sq	0.150	0.195	0.957	0.956

Notes: This table presents regression estimates of the heterogeneous effects of corporate site visits on local air pollution, distinguishing between firms based on industry pollution characteristics. The sample consists of daily observations at the site level from January 1, 2012, to December 31, 2019. The dependent variable in columns (1) and (2) is $Pollution^{abn}$, defined as the difference between the average PM2.5 concentration within a 1km radius of the site ($Pollution$) and the average concentration within a surrounding 1km to 3km buffer ring ($Pollution^{ring}$). In columns (3) and (4), the dependent variable is the raw pollution level ($Pollution$). The sample is split into two groups based on industry type: “High-pollution industries” (thermal power, iron and steel, cement, electrolytic aluminum, coal, metallurgy, chemicals, petrochemicals, building materials, paper, brewing, pharmaceuticals, fermentation, textiles, tanning, and mining) and “Low-pollution industries” (the remaining industries). The primary independent variable is $SiteVisit^{3day}$. The difference between the coefficients of the subsamples and the p-value from a test of their equality are reported. All models include controls for concurrent surrounding pollution ($Pollution^{ring}$) and lagged pollution ($Pollution^{lag}$), calculated as the average pollution level over the pre-event window [*t*-14, *t*-7], alongside site and city-date fixed effects. All variables are defined in Appendix 1. Standard errors are clustered at the site level and are shown in parentheses, with *, **, and *** denoting statistical significance at the 10%, 5%, and 1% levels, respectively.

Table 4: The heterogeneous effects of site visits by firm valuation

	(1)	(2)	(3)	(4)
Dependent variable	*Pollution*^{abn}		*Pollution*	
Subsample	High *Tobin's Q*	Low *Tobin's Q*	High *Tobin's Q*	Low *Tobin's Q*
SiteVisit^{3day}	-0.027***	-0.000	-0.030***	-0.000
	(0.007)	(0.010)	(0.008)	(0.010)
Difference between the coefficients of *SiteVisit*^{3day}	(2)-(1): 0.027 p-value: 0.000		(4)-(3): 0.030 p-value: 0.000	
Controls	Yes	Yes	Yes	Yes
Site FE	Yes	Yes	Yes	Yes
City-date FE	Yes	Yes	Yes	Yes
N	3,906,963	3,001,757	3,906,963	3,001,757
Adj. R-sq	0.171	0.185	0.956	0.958

Notes: This table presents regression estimates of the heterogeneous effects of corporate site visits on local air pollution, distinguishing between firms based on market valuation. The sample consists of daily observations at the site level from January 1, 2012, to December 31, 2019. The dependent variable in columns (1) and (2) is *Pollution*^{abn}, defined as the difference between the average PM2.5 concentration within a 1km radius of the site (*Pollution*) and the average concentration within a surrounding 1km to 3km buffer ring (*Pollution*^{ring}). In columns (3) and (4), the dependent variable is the raw pollution level (*Pollution*). The sample is split into two groups based on firm valuation: "High *Tobin's Q*" (Tobin's Q above the median) and "Low *Tobin's Q*" (Tobin's Q below the median). The primary independent variable is *SiteVisit*^{3day}. The difference between the coefficients of the subsamples and the p-value from a test of their equality are reported. All models include controls for concurrent surrounding pollution (*Pollution*^{ring}) and lagged pollution (*Pollution*^{lag}), calculated as the average pollution level over the pre-event window [*t*-14, *t*-7], alongside site and city-date fixed effects. All variables are defined in Appendix 1. Standard errors are clustered at the site level and are shown in parentheses, with *, **, and *** denoting statistical significance at the 10%, 5%, and 1% levels, respectively.

Table 5: The heterogeneous effects of site visits by ESG ratings

Panel A: Subgroup by composite ESG rating

	(1)	(2)	(3)	(4)
Dependent variable	$Pollution^{abn}$		$Pollution$	
Subsample	High ESG Rating	Low ESG Rating	High ESG Rating	Low ESG Rating
$SiteVisit^{3day}$	-0.009	-0.019***	-0.009	-0.021***
	(0.009)	(0.007)	(0.010)	(0.008)
Difference between the coefficients of $SiteVisit^{3day}$	(2)-(1): -0.010 P-value: 0.100		(4)-(3): -0.012 P-value: 0.070	
Controls	Yes	Yes	Yes	Yes
Site FE	Yes	Yes	Yes	Yes
City-date FE	Yes	Yes	Yes	Yes
N	2,949,944	3,958,776	2,949,944	3,958,776
Adj. R-sq	0.174	0.178	0.959	0.955

Panel B: Subgroup by E rating

	(1)	(2)	(3)	(4)
Dependent variable	$Pollution^{abn}$		$Pollution$	
Subsample	High E Rating	Low E Rating	High E Rating	Low E Rating
$SiteVisit^{3days}$	0.010	-0.016***	0.011	-0.017***
	(0.024)	(0.006)	(0.024)	(0.006)
Difference between the coefficients $SiteVisit^{3day}$	(2)-(1): -0.026 p-value: 0.010		(4)-(3): -0.028 p-value: 0.010	
Controls	Yes	Yes	Yes	Yes
Site FE	Yes	Yes	Yes	Yes
City-date FE	Yes	Yes	Yes	Yes
N	1,093,913	5,814,807	1,093,913	5,814,807
Adj. R-sq	0.188	0.163	0.956	0.957

Panel C: Subgroup by S rating

	(1)	(2)	(3)	(4)
Dependent variable	$Pollution^{abn}$		$Pollution$	
Subsample	High S Rating	Low S Rating	High S Rating	Low S Rating
$SiteVisit^{3days}$	-0.011	-0.013*	-0.011	-0.015*
	(0.008)	(0.008)	(0.009)	(0.008)
Difference between the coefficients of $SiteVisit^{3day}$	(2)-(1): -0.002 p-value: 0.400		(4)-(3): -0.004 p-value: 0.290	
Controls	Yes	Yes	Yes	Yes
Site FE	Yes	Yes	Yes	Yes
City-date FE	Yes	Yes	Yes	Yes
N	3,469,696	3,439,024	3,469,696	3,439,024
Adj. R-sq	0.168	0.183	0.960	0.954

Panel D: Subgroup by G rating

	(1)	(2)	(3)	(4)

Dependent variable	*Pollution*^{abn}		*Pollution*	
Subsample	High G Rating	Low G Rating	High G Rating	Low G Rating
SiteVisit^{3days}	-0.020***	-0.009	-0.022***	-0.004
	(0.006)	(0.013)	(0.007)	(0.013)
Difference between the coefficients of *SiteVisit*^{3day}	(2)-(1): 0.011 p-value: 0.220		(4)-(3): 0.018 p-value: 0.060	
Controls	Yes	Yes	Yes	Yes
Site FE	Yes	Yes	Yes	Yes
City-date FE	Yes	Yes	Yes	Yes
N	5,567354	1,341,366	5,567,354	1,341,366
Adj. R-sq	0.161	0.235	0.957	0.956

Notes: This table presents regression estimates of the heterogeneous effects of corporate site visits on local air pollution, distinguishing between firms based on ESG performance. The dependent variable in columns (1) and (2) is *Pollution*^{abn}, defined as the difference between the average PM2.5 concentration within a 1km radius of the site (*Pollution*) and the average concentration within a surrounding 1km to 3km buffer ring (*Pollution*^{ring}). In columns (3) and (4), the dependent variable is the raw pollution level (*Pollution*). The primary independent variable is *SiteVisit*^{3day}. The sample is split into two groups based on Sino-Securities Index Bond ESG rating: Panel A compares firms with high composite ESG rating versus low ESG rating; Panel B compares firms with high E rating versus low E rating; Panel C compares high S rating versus low S rating; and Panel D compares high G rating versus low G rating. For each category, a “high” rating denotes a score higher than 4, while a “low” rating denotes a score equal to or lower than 4. The difference between the coefficients of the subsamples and the p-value from a test of their equality are reported. All models include controls for concurrent surrounding pollution (*Pollution*^{ring}) and lagged pollution (*Pollution*^{lag}), calculated as the average pollution level over the pre-event window [*t*-14, *t*-7], alongside site and city-date fixed effects. All variables are defined in Appendix 1. Standard errors are clustered at the site level and are shown in parentheses, with *, **, and *** denoting statistical significance at the 10%, 5%, and 1% levels, respectively.

Table 6: The heterogeneous effects of site visits by governance

Panel A: Internal governance: Managerial compensation

	(1)	(2)	(3)	(4)
Dependent variable	$Pollution^{abn}$		$Pollution$	
Subsample	Low *ExePay*	High *ExePay*	Low *ExePay*	High *ExePay*
$SiteVisit^{3day}$	-0.019**	-0.011	-0.022**	-0.010
	(0.009)	(0.008)	(0.010)	(0.008)
Difference between the coefficients of $SiteVisit^{3day}$	(2)-(1): 0.008 p-value: 0.110		(4)-(3): 0.0103 p-value: 0.070	
Controls	Yes	Yes	Yes	Yes
Site FE	Yes	Yes	Yes	Yes
City-date FE	Yes	Yes	Yes	Yes
N	3,111,248	3,797,472	3,111,248	3,797,472
Adj. R-sq	0.178	0.166	0.957	0.956

Panel B: External governance: Institutional ownership

	(1)	(2)	(3)	(4)
Dependent variable	$Pollution^{abn}$		$Pollution$	
Subsample	Low *IO*	High *IO*	Low *IO*	High *IO*
$SiteVisit^{3day}$	-0.008	-0.019**	-0.009	-0.019**
	(0.008)	(0.008)	(0.009)	(0.009)
Difference between the coefficients of $SiteVisit^{3day}$	(2)-(1): 0.011 p-value: 0.080		(4)-(3): 0.010 p-value: 0.100	
Controls	Yes	Yes	Yes	Yes
Site FE	Yes	Yes	Yes	Yes
City-date FE	Yes	Yes	Yes	Yes
N	3,038,865	3,869,855	3,038,865	3,869,855
Adj. R-sq	0.190	0.166	0.958	0.956

Notes: This table presents regression estimates of the heterogeneous effects of corporate site visits on local air pollution, distinguishing between internal and external governance mechanisms. The sample consists of daily observations at the site level from January 1, 2012, to December 31, 2019. Panel A focuses on internal governance proxied by managerial compensation (*ExePay*), defined as the logarithm of one plus the total compensation of the top three executives. Panel B focuses on external governance proxied by institutional ownership (*IO*), measured as the number of shares held by institutional investors divided by the total number of shares outstanding. The dependent variable in columns (1) and (2) is $Pollution^{abn}$, defined as the difference between the average PM2.5 concentration within a 1km radius of the site (*Pollution*) and the average concentration within a surrounding 1km to 3km buffer ring ($Pollution^{ring}$). In columns (3) and (4), the dependent variable is the raw pollution level (*Pollution*). The sample is split into two subsamples based on whether the governance variable is above or below the median. The primary independent variable is $SiteVisit^{3day}$. The difference between the coefficients of the subsamples and the p-value from a test of their equality are reported. All models include controls for concurrent surrounding pollution ($Pollution^{ring}$) and lagged pollution ($Pollution^{lag}$), calculated as the average pollution level over the pre-event window [*t*-14, *t*-7], alongside site and city-date fixed effects. All variables are defined in Appendix 1. Standard errors are clustered at the site level and are shown in parentheses, with *, **, and *** denoting statistical significance at the 10%, 5%, and 1% levels, respectively.

Table 7: Visitor ownership stake and PRI signatory

Panel A: Stake visitors

	(1)	(2)	(3)	(4)
Dependent variable	$Pollution^{abn}$		*Pollution*	
Stake	-0.040**		-0.040**	
	(0.016)		(0.018)	
nonStake	-0.010		-0.009	
	(0.008)		(0.009)	
Stake_Num		-0.018*		-0.019*
		(0.010)		(0.011)
nonStake_Num		-0.000		-0.000
		(0.000)		(0.000)
Difference between *Stake* and *nonStake*	-0.031 p-value: 0.080		-0.031 p-value: 0.124	
Difference between *Stake_Num* and *nonStake_Num*		-0.018 p-value: 0.080		-0.018 p-value: 0.103
Controls	Yes	Yes	Yes	Yes
Site FE	Yes	Yes	Yes	Yes
City-date FE	Yes	Yes	Yes	Yes
N	6,908,720	6,908,720	6,908,720	6,908,720
Adj. R-sq	0.156	0.156	0.957	0.957

Panel B: PRI visitors

	(1)	(2)	(3)	(4)
Dependent variable	$Pollution^{abn}$		*Pollution*	
PRI	-0.013		-0.013	
	(0.010)		(0.011)	
nonPRI	-0.018*		-0.017	
	(0.011)		(0.012)	
PRI_Num		-0.001		-0.001
		(0.002)		(0.002)
nonPRI_Num		-0.001		-0.000
		(0.000)		(0.000)
Difference between *PRI* and *nonPRI*	0.005 p-value: 0.704		0.004 p-value: 0.814	
Difference between *PRI_Num* and *nonPRI_Num*		-0.000 p-value: 0.833		-0.000 p-value: 0.833
Controls	Yes	Yes	Yes	Yes
Site FE	Yes	Yes	Yes	Yes
City-date FE	Yes	Yes	Yes	Yes
N	6,908,720	6,908,720	6,908,720	6,908,720
Adj. R-sq	0.156	0.156	0.957	0.957

Panel C: Horse race between stake and PRI visitors

	(1)	(2)	(3)	(4)
Dependent variable	$Pollution^{abn}$		*Pollution*	
Stake	-0.046**		-0.044**	

	(0.019)		(0.022)	
nonStake	-0.014		-0.012	
	(0.011)		(0.013)	
Stake_Num		-0.020*		-0.020
		(0.011)		(0.012)
nonStake_Num		-0.000		-0.000
		(0.000)		(0.000)
PRI	0.008		0.006	
	(0.014)		(0.016)	
PRI_num		0.001		0.001
		(0.002)		(0.003)
Difference between *Stake* and *nonStake*	-0.032 p-value: 0.074		-0.032 p-value: 0.117	
Difference between *Stake_Num* and *nonStake_Num*		-0.019 p-value: 0.086		-0.019 p-value: 0.108
Controls	Yes	Yes	Yes	Yes
Site FE	Yes	Yes	Yes	Yes
City-date FE	Yes	Yes	Yes	Yes
N	6,908,720	6,908,720	6,908,720	6,908,720
Adj. R-sq	0.156	0.156	0.957	0.957

Notes: This table presents regression estimates of the effect of visitors' ownership stake and PRI signatory on local air pollution. The sample consists of daily observations at the site level from January 1, 2012, to December 31, 2019. The dependent variable in columns (1) and (2) is $Pollution^{abn}$, defined as the difference between the average PM2.5 concentration within a 1km radius of the site (*Pollution*) and the average concentration within a surrounding 1km to 3km buffer ring ($Pollution^{ring}$). In columns (3) and (4), the dependent variable is the raw pollution level (*Pollution*). Panel A distinguishes visits based on stake status, where *Stake* (*nonStake*) equals one if the visiting group includes (does not include) a shareholder. Panel B distinguishes visits based on PRI status, where *PRI* (*nonPRI*) equals one if the group includes (does not include) a PRI signatory. Panel C presents a horse race including both categories. The variables suffixed with *_Num* represent the count of visitors in each respective category. The differences between coefficients and the corresponding p-values for tests of equality are reported. All models include controls for concurrent surrounding pollution ($Pollution^{ring}$) and lagged pollution ($Pollution^{lag}$), calculated as the average pollution level over the pre-event window [*t*-14, *t*-7], alongside site and city-date fixed effects. All variables are defined in Appendix 1. Standard errors are clustered at the site level and are shown in parentheses, with *, **, and *** denoting statistical significance at the 10%, 5%, and 1% levels, respectively.

Table 8: The effects on sister non-visited sites

Panel A: Sites of the same company in the same city

	(1)	(2)	(3)	(4)
Dependent variable	$Pollution^{abn}$		$Pollution$	
$SameCity$	0.006		0.008	
	(0.008)		(0.008)	
$SameCity^{3day}$		0.005		0.006
		(0.006)		(0.006)
Controls	Yes	Yes	Yes	Yes
Site FE	Yes	Yes	Yes	Yes
City-date FE	Yes	Yes	Yes	Yes
Adj. R-sq	0.156	0.156	0.957	0.957
N	6,908,720	6,908,720	6,908,720	6,908,720

Panel B: Sites of the same company in different cities

	(1)	(2)	(3)	(4)
Dependent variable	$Pollution^{abn}$		$Pollution$	
$DiffCity$	-0.007		-0.010	
	(0.013)		(0.014)	
$DiffCity^{3day}$		-0.015		-0.017
		(0.009)		(0.011)
Controls	Yes	Yes	Yes	Yes
Site FE	Yes	Yes	Yes	Yes
City-date FE	Yes	Yes	Yes	Yes
Adj. R-sq	0.156	0.156	0.957	0.957
N	6,908,720	6,908,720	6,908,720	6,908,720

Notes: This table presents the regression estimates examining the effects of site visits on pollution on other sites within the same company. The sample consists of daily observations at the site level from January 1, 2012, to December 31, 2019. The dependent variable in columns (1) and (2) is $Pollution^{abn}$, defined as the difference between the average PM2.5 concentration within a 1km radius of the site (*Pollution*) and the average concentration within a surrounding 1km to 3km buffer ring ($Pollution^{ring}$). In columns (3) and (4), the dependent variable is the raw pollution level (*Pollution*). Panel A reports estimates for non-visited sites belonging to the same firm and located in the same city as the visited site (*SameCity* and $SameCity^{3day}$). Panel B reports estimates for non-visited sites belonging to the same firm but located in a different city (*DiffCity* and $DiffCity^{3day}$). *SameCity* and *DiffCity* indicate the observations of non-visited sites for day *t,* while $SameCity^{3day}$ and $DiffCity^{3day}$ indicate the observations of non-visited sites in the 3-day window (from days *t*-1 to *t*+1). All models include controls for concurrent surrounding pollution ($Pollution^{ring}$) and lagged pollution ($Pollution^{lag}$), calculated as the average pollution level over the pre-event window [*t*-14, *t*-7], alongside site and city-date fixed effects. All variables are defined in Appendix 1. Standard errors are clustered at the site level and are shown in parentheses, with *, **, and *** denoting statistical significance at the 10%, 5%, and 1% levels, respectively.

Table 9: Change in operational activities

	(1)	(2)	(3)	(4)
Dependent variable	*TIR*		*AR*	
SiteVisit	0.012		-0.005	
	(0.018)		(0.016)	
$SiteVisit^{3day}$		0.000		-0.004
		(0.012)		(0.010)
Controls	Yes	Yes	Yes	Yes
Site FE	Yes	Yes	Yes	Yes
City-date FE	Yes	Yes	Yes	Yes
N	712,027	712,027	712,027	712,027
Adj. R-sq	0.987	0.987	0.668	0.668

Notes: This table presents the regression estimates of the effect of corporate site visits on firms' operating activities, using a sample of daily observations at the site level from January 1, 2012, to December 31, 2019. The dependent variable in columns (1) and (2) is *TIR*, defined as the average daytime thermal infrared radiation value of the site on day *t*. The dependent variable in columns (3) and (4) is *AR*, calculated as the difference between the average *TIR* of the site and that of a buffer zone within 5km on day *t*. The primary independent variables are *SiteVisit*, an indicator equal to one if the site was visited on day *t*, and $SiteVisit^{3day}$, an indicator equal to one if a visit occurred on day *t*-1, *t*, or *t*+1. All models include controls for the area size of the site (*SiteAreaSize*) and the lagged *TIR*/*AR*, calculated as the average *TIR*/*AR* over the pre-event window [*t*-14, *t*-7], alongside site and city-date fixed effects. All variables are defined in Appendix 1. Standard errors are clustered at the site level and are shown in parentheses, with *, **, and *** denoting statistical significance at the 10%, 5%, and 1% levels, respectively.

Table 10: The effect of installed-abatement capacity

	(1)	(2)	(3)	(4)
Dependent variable	$Pollution^{abn}$		$Pollution$	
Subsample	Low *IAC*	High *IAC*	Low *IAC*	High *IAC*
$SiteVisit^{3day}$	-0.010*	-0.039**	-0.012*	-0.038**
	(0.006)	(0.017)	(0.007)	(0.019)
Difference between the coefficients of	(2)-(1): -0.029		(4)-(3): -0.026	
$SiteVisit^{3day}$	P-value: 0.000		P-value: 0.000	
Controls	Yes	Yes	Yes	Yes
Site FE	Yes	Yes	Yes	Yes
City-date FE	Yes	Yes	Yes	Yes
N	5,319,138	1,589,582	5,319,138	1,589,582
Adj. R-sq	0.169	0.175	0.955	0.960

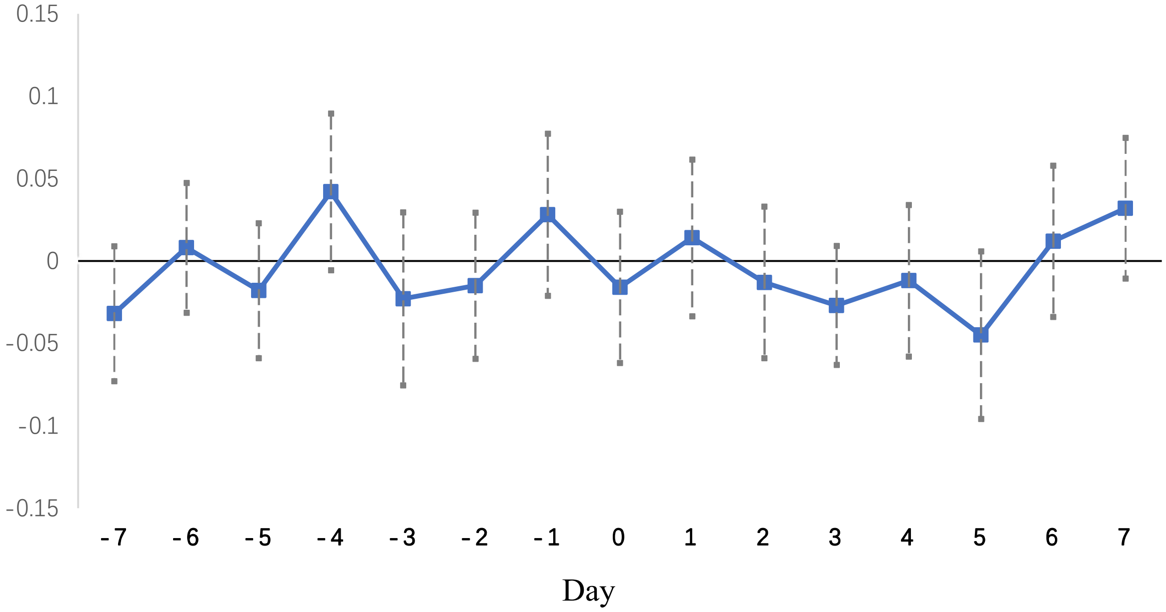
Notes: This table presents regression estimates of the effects of corporate site visits on local air pollution, distinguishing between firms based on installed-abatement capacity (*IAC*). The sample consists of daily observations at the site level from January 1, 2012, to December 31, 2019. The dependent variable in columns (1) and (2) is $Pollution^{abn}$, defined as the difference between the average PM2.5 concentration within a 1km radius of the site (*Pollution*) and the average concentration within a surrounding 1km to 3km buffer ring ($Pollution^{ring}$). In columns (3) and (4), the dependent variable is the raw pollution level (*Pollution*). *IAC* is measured from the intensity of pollution-abatement discussion in a firm's annual report MD&A; high *IAC* firms mention keywords "desulfurization," "denitrification", "dust collector", "environmental protection equipment", and "pollution control equipment", while low *IAC* firms do not. The primary independent variable is $SiteVisit^{3day}$. The difference between the coefficients of the subsamples and the p-value from a test of their equality are reported. All models include controls for concurrent surrounding pollution ($Pollution^{ring}$) and lagged pollution ($Pollution^{lag}$), calculated as the average pollution level over the pre-event window [*t*-14, *t*-7], alongside site and city-date fixed effects. All variables are defined in Appendix 1. Standard errors are clustered at the site level and are shown in parentheses, with *, **, and *** denoting statistical significance at the 10%, 5%, and 1% levels, respectively.

Internet Appendix

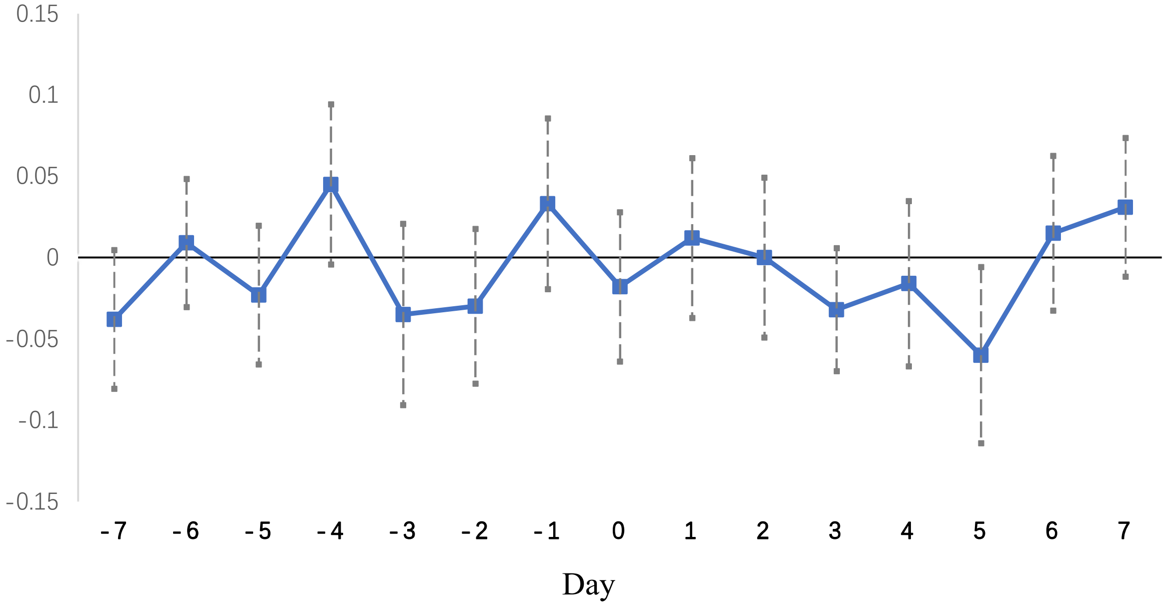
Seeing Is Not Believing: Strategic Pollution Suppression Around Corporate Site Visits

Figure IA1: Dynamic impacts of online visits on local air pollution over a 14-day window

Panel A: Abnormal pollution, *Pollution*^{abn}



Panel B: Average pollution, *Pollution*



Notes: This figure illustrates the dynamic effects of online site visits on local air pollution across a 14-day window surrounding the event. The analysis plots the estimated coefficients and corresponding confidence intervals (90%) for a series of dummy variables representing specific days relative to the site visit, ranging from 7 days before (*t*-7) to 7 days after (*t*+7) the event. Panel A displays the results for abnormal pollution (*Pollution*^{abn}), while Panel B shows the results for average pollution (*Pollution*). The horizontal axis represents the timeline relative to the visit day (Day 0), and the vertical axis indicates the magnitude of the estimated impact on pollution levels.

Table IA1: Sample distribution by CSRC 2012 industry classification guidelines

Code	Industry name	Freq.	Percent
	Food, Beverage, and Tobacco		
C13	Agricultural Food Processing Industry	34	2.4
C14	Food Manufacturing	17	1.2
C15	Wine, Beverage and Refined Tea Manufacturing Industry	13	0.92
	Textile, Apparel, and Footwear		
C17	Textile Industry	20	1.41
C18	Textile, Clothing and Apparel Industry	26	1.84
C19	Leather, fur, feather and their products and footwear industry	3	0.21
	Wood and Furniture		
C20	Wood processing and wood, bamboo, rattan, palm and grass products industry	5	0.35
C21	Furniture Manufacturing	9	0.64
	Paper, Printing, and Cultural Products		
C22	Paper-making and paper products industry	15	1.06
C23	Printing and recording media reproduction industry	6	0.42
C24	Cultural, educational, industrial and aesthetic, sports and recreational goods manufacturing industry	12	0.85
	Petroleum, Chemical, and Biopharmaceutical		
C25	Petroleum Processing, Coking and Nuclear Fuel Processing Industry	7	0.5
C26	Chemical raw materials and chemical products manufacturing	144	10.18
C27	Pharmaceutical Manufacturing	125	8.84
C28	Chemical Fiber Manufacturing	16	1.13
C29	Rubber and plastic products industry	52	3.68
	Metal and Non-metal		
C30	Non-metallic Mineral Products Industry	51	3.61
C31	Ferrous Metals Smelting and Calendaring Industry	11	0.78
C32	Nonferrous Metals Smelting and Calendaring Industry	38	2.69
C33	Metal Products Industry	41	2.9
	Specialized, General, and Transportation Equipment		
C34	General Equipment Manufacturing	92	6.51
C35	Special Purpose Equipment Manufacturing	142	10.04
C36	Automobile Manufacturing	55	3.89
C37	Railway, Shipbuilding, Aerospace and Other Transportation Equipment Manufacturing Industry	20	1.41
	Electrical, Electronic, and Communication Equipment		
C38	Electrical Machinery and Equipment Manufacturing	153	10.82
C39	Computer, communications and other electronic equipment manufacturing	246	17.4
	Instruments and Meters		
C40	Instrumentation Manufacturing	41	2.9
	Other Manufacturing Industries		
C41	Other manufacturing industries	18	1.27
C42	Waste Resources Comprehensive Utilization Industry	2	0.14
Total		1,414	100

Table IA2: Summary statistics

Variable	N	Mean	SD	P25	Median	P75
Outcome variables:						
Pollution	6,908,720	49.573	34.539	26.50	40.43	61.55
Pollution^{abn}	6,908,720	0.093	1.209	-0.42	0.03	0.55
Pollution^{lag}	6,908,720	49.857	28.378	30.01	43.05	62.24
Pollution^{ring}	6,908,720	49.479	34.383	26.49	40.37	61.40
TIR	708,311	296.448	11.037	288.70	298.25	305.20
AR	708,311	1.350	1.844	0.16	1.14	2.39
Key independent variables:						
SiteVisit	6,908,720	0.004	0.067	0.00	0.00	0.00
Sitevisit^{3day}	6,908,720	0.013	0.111	0.00	0.00	0.00
Visitor type indicators:						
Advisor	6,908,720	0.000	0.009	0.00	0.00	0.00
Advisor^{3day}	6,908,720	0.000	0.016	0.00	0.00	0.00
Assman	6,908,720	0.002	0.043	0.00	0.00	0.00
Assman^{3day}	6,908,720	0.005	0.074	0.00	0.00	0.00
Bank	6,908,720	0.000	0.011	0.00	0.00	0.00
Bank^{3day}	6,908,720	0.000	0.019	0.00	0.00	0.00
Foreign	6,908,720	0.001	0.025	0.00	0.00	0.00
Foreign^{3day}	6,908,720	0.002	0.043	0.00	0.00	0.00
Funds	6,908,720	0.003	0.052	0.00	0.00	0.00
Funds^{3day}	6,908,720	0.008	0.089	0.00	0.00	0.00
Futures	6,908,720	0.000	0.005	0.00	0.00	0.00
Futures^{3day}	6,908,720	0.000	0.008	0.00	0.00	0.00
Individual	6,908,720	0.000	0.012	0.00	0.00	0.00
Individual^{3day}	6,908,720	0.000	0.020	0.00	0.00	0.00
Insurance	6,908,720	0.000	0.020	0.00	0.00	0.00
Insurance^{3day}	6,908,720	0.001	0.035	0.00	0.00	0.00
Media	6,908,720	0.000	0.009	0.00	0.00	0.00
Media^{3day}	6,908,720	0.000	0.016	0.00	0.00	0.00
Securities	6,908,720	0.004	0.060	0.00	0.00	0.00
Securities^{3day}	6,908,720	0.010	0.101	0.00	0.00	0.00
Others	6,908,720	0.000	0.008	0.00	0.00	0.00
Others^{3day}	6,908,720	0.000	0.013	0.00	0.00	0.00
Other visit characteristics:						
Ln(# Word)	6,908,720	0.031	0.468	0.00	0.00	0.00
Ln(# Institution)	6,908,720	0.007	0.124	0.00	0.00	0.00
Ln(# Researcher)	6,908,720	0.007	0.125	0.00	0.00	0.00
Online	6,908,720	0.000	0.014	0.00	0.00	0.00
Stake	6,908,720	0.001	0.028	0.00	0.00	0.00
nonStake	6,908,720	0.004	0.060	0.00	0.00	0.00
Stake_Num	6,908,720	0.001	0.045	0.00	0.00	0.00
nonStake_Num	6,908,720	0.034	1.449	0.00	0.00	0.00
PRI	6,908,720	0.002	0.049	0.00	0.00	0.00
nonPRI	6,908,720	0.002	0.045	0.00	0.00	0.00
PRI_Num	6,908,720	0.008	0.235	0.00	0.00	0.00
nonPRI_Num	6,908,720	0.027	1.362	0.00	0.00	0.00
SameCity	6,908,720	0.004	0.059	0.00	0.00	0.00
SameCity^{3day}	6,908,720	0.010	0.099	0.00	0.00	0.00

DiffCity	6,908,720	0.002	0.039	0.00	0.00	0.00
DiffCity^{3day}	6,908,720	0.004	0.066	0.00	0.00	0.00
Other variables:						
ESG Rating	6,908,720	4.174	1.032	4.00	4.00	5.00
E Rating	6,908,720	2.340	1.501	1.00	2.00	3.00
S Rating	6,908,720	4.289	1.581	3.00	5.00	5.00
G Rating	6,908,720	5.230	1.310	5.00	5.00	6.00
HighPollution	6,908,720	0.317	0.465	0.00	0.00	1.00
Tobin's Q	6,908,720	2.141	1.320	1.40	1.90	2.31
ExePay	6,908,720	14.354	0.669	13.96	14.35	14.69
IO	6,908,720	34.826	23.321	13.39	34.83	52.38
IAC	6,908,720	0.000	0.001	0.00	0.00	0.00

Table IA3: Oster delta statistic analysis

Dependent variable	Independent variable	Delta	R-squared (uncontrolled):	R-squared (controlled):
$Pollution^{abn}$	$SiteVisit$	1.11198	0.000	0.225
$Pollution^{abn}$	$SiteVisit^{3day}$	1.63392	0.000	0.225
$Pollution$	$SiteVisit$	-35.45095	0.000	0.957
$Pollution$	$SiteVisit^{3day}$	-22.34914	0.000	0.957

Notes: The table reports the calculated Delta statistic of Oster (2019), along with the uncontrolled and controlled R-squared values, for our baseline regression models where the dependent variables are $Pollution^{abn}$ and $Pollution$, and the independent variables are $SiteVisit$ and $SiteVisit^{3day}$. Controls include concurrent surrounding pollution ($Pollution^{ring}$) and lagged pollution ($Pollution^{lag}$), alongside site and city-date fixed effects. All variables are defined in Appendix 1.

Table IA4: Entropy balancing approach

	(1)	(2)	(3)	(4)
Dependent variable	$Pollution^{abn}$		$Pollution$	
SiteVisit	-0.013*		-0.015**	
	(0.007)		(0.008)	
$SiteVisit^{3day}$		-0.014*		-0.016**
		(0.007)		(0.008)
Controls	Yes	Yes	Yes	Yes
Site FE	Yes	Yes	Yes	Yes
City-date FE	Yes	Yes	Yes	Yes
N	6,908,720	6,908,720	6,908,720	6,908,720
Adj. R-sq	0.419	0.419	0.955	0.955

Notes: This table presents the baseline regression estimates using an entropy balancing approach (Hainmueller, 2012; Hainmueller and Xu, 2013). The dependent variable in columns (1) and (2) is $Pollution^{abn}$, defined as the difference between the average PM2.5 concentration within a 1km radius of the site (*Pollution*) and the average concentration within a surrounding 1km to 3km buffer ring ($Pollution^{ring}$). In columns (3) and (4), the dependent variable is the raw pollution level (*Pollution*). The primary independent variables are *SiteVisit*, an indicator equal to one if the site was visited on day *t*, and $SiteVisit^{3day}$, an indicator equal to one if a visit occurred on day *t*-1, *t*, or *t*+1. The analysis constructs a counterfactual control group in which we assign a weight (between 0 and 1) to each observation so that the variables we incorporate as matching dimensions (mainly place and time) are balanced with or without site visit. All models include controls for concurrent surrounding pollution ($Pollution^{ring}$) and lagged pollution ($Pollution^{lag}$), calculated as the average pollution level over the pre-event window [*t*-14, *t*-7], alongside site and city-date fixed effects. All variables are defined in Appendix 1. Standard errors are clustered at the site level and are shown in parentheses, with *, **, and *** denoting statistical significance at the 10%, 5%, and 1% levels, respectively.

Table IA5: Geographic variation

Panel A: Excluding provincial capitals and municipalities

	(1)	(2)	(3)	(4)
Dependent variable	$Pollution^{abn}$		$Pollution$	
SiteVisit	-0.016*		-0.016	
	(0.009)		(0.010)	
$SiteVisit^{3day}$		-0.012*		-0.013*
		(0.007)		(0.008)
Controls	Yes	Yes	Yes	Yes
Site FE	Yes	Yes	Yes	Yes
City-date FE	Yes	Yes	Yes	Yes
N	4,146,400	4,146,400	4,146,400	4,146,400
Adj. R-sq	0.186	0.186	0.952	0.952

Panel B: Exclude southern provinces

	(1)	(2)	(3)	(4)
Dependent variable	$Pollution^{abn}$		$Pollution$	
SiteVisit	-0.032*		-0.027	
	(0.017)		(0.020)	
$SiteVisit^{3day}$		-0.036***		-0.040***
		(0.013)		(0.015)
Controls	Yes	Yes	Yes	Yes
Site FE	Yes	Yes	Yes	Yes
City-date FE	Yes	Yes	Yes	Yes
N	1,810,400	1,810,400	1,810,400	1,810,400
Adj. R-sq	0.158	0.158	0.966	0.966

Panel C: Exclude coastal provinces

	(1)	(2)	(3)	(4)
Dependent variable	$Pollution^{abn}$		$Pollution$	
SiteVisit	-0.036**		-0.031*	
	(0.016)		(0.019)	
$SiteVisit^{3day}$		-0.033***		-0.034**
		(0.012)		(0.013)
Controls	Yes	Yes	Yes	Yes
Site FE	Yes	Yes	Yes	Yes
City-date FE	Yes	Yes	Yes	Yes
N	1,988,520	1,988,520	1,988,520	1,988,520
Adj. R-sq	0.144	0.144	0.962	0.962

Notes: This table presents geographic variation of the baseline results. The dependent variable in columns (1) and (2) is $Pollution^{abn}$, defined as the difference between the average PM2.5 concentration within a 1km radius of the site (*Pollution*) and the average concentration within a surrounding 1km to 3km buffer ring ($Pollution^{ring}$). In columns (3) and (4), the dependent variable is the raw pollution level (*Pollution*). The primary independent variables are *SiteVisit*, an indicator equal to one if the site was visited on day t, and $SiteVisit^{3day}$, an indicator equal to one if a visit occurred on day t-1, t, or t+1. Panel A excludes provincial capitals and municipalities; Panel B excludes southern provinces (Shanghai, Anhui, Guangdong, Jiangxi, Guangxi Zhuang Autonomous Region, Jiangsu, Hubei, Zhejiang, Hainan, Fujian, Yunnan, Guizhou, Sichuan, and Chongqing); and Panel C excludes coastal provinces (Shanghai, Liaoning, Guangdong, Guangxi Zhuang Autonomous Region, Jiangsu, Zhejiang, Hainan, Fujian, Tianjin, Hebei, and Shandong). All models include controls for concurrent surrounding pollution ($Pollution^{ring}$) and lagged pollution ($Pollution^{lag}$), calculated as the average pollution level over the pre-event window [*t*-14, *t*-7], alongside site and city-date fixed effects. All variables are defined in Appendix 1. Standard errors are clustered at the site level and are shown in parentheses, with *, **, and *** denoting statistical significance at the 10%, 5%, and 1% levels, respectively.