E vs. G: Environmental Policy and Earnings Management in China*

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March 2025

Abstract

We find evidence that firms engage in earnings management to potentially diminish environmental regulatory attention after the implementation of an automatic air pollutant monitoring system in China. Polluting firms increase their use of discretionary accruals and reduce the informativeness of earnings, compared to non-polluting firms. Polluting firms that are larger, more profitable, located near monitoring stations, and situated in less market-oriented regions exhibit heightened earnings management, consistent with the greater environmental regulatory exposure these firms face. The behavior is moderated by stronger customer-supplier relationships and lower market competition, when the cost of earnings management is higher. Our findings highlight the conflict between environmental and governance issues.

JEL Classification: G34, G38, Q53, Q58

Keywords: ESG, Environmental Regulations, Accrual-Based Earnings Management, Corporate Governance, Automatic Monitoring System

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1 Introduction

The concept of Environmental, Social, and Governance (ESG) became widely recognized in a 2004 report by the United Nations.[1] Since then, it has gained significant attention from both professionals and academics. Although firms' ESG has generally improved over time, conflicts can arise within the E, S, and G dimensions. For example, in 2015, Volkswagen installed software in diesel engines to cheat emission tests to appear environmentally friendly. This decision led to serious governance issues, including legal and financial repercussions. However, there is limited direct evidence of such conflicts. While one might argue that a company prioritizing environmental sustainability could cut spending on safety and labor standards, proving a causal link between the E, S, and G dimensions is difficult. Additionally, ESG ratings from various agencies may be based on different criteria or the same criteria with different indicators (Berg et al. (2022)), complicating the understanding of how these three pillars relate. In this paper, we present systematic evidence of a conflict between E and G arising from an environmental policy change in China.

As a pivotal part of the Chinese central government's "War on Pollution," the Ministry of Environmental Protection (currently the Ministry of Ecology and Environment, MEE) announced the establishment of an automatic air pollutant monitoring system in 2012. This system enables real-time data transmission from monitoring equipment to the central government and the public, making it much harder for local governments to manipulate air quality data. Continuous, automatic monitoring prevents local authorities from selectively reporting less polluted days or times to the central government.[2] Research by Greenstone et al. (2022) and Barwick et al. (2024) highlights the effectiveness of this policy. Greenstone et al. (2022) show that reported PM_{10} concentrations rose by 35% immediately after

[1] The United Nations Global Compact released the report "Who Cares Wins" in 2004. Endorsed by over 20 financial institutions, the report develops guidelines and recommendations on how to better integrate ESG issues in asset management, securities brokerage services, and associated research functions.

[2] As noted by Greenstone et al. (2022), a notable aspect of China's political system is that local officials receive strong incentives to meet specific economic and social targets, connecting their performance in these areas to their career advancement. Although this incentive structure can effectively drive target achievement, it also encourages dishonest behavior.

automation and remained elevated, indicating improved information transparency following the reform. Barwick et al. (2024) find that the program increased public awareness of pollution issues, leading to behavioral changes such as avoidance of outdoor exposure and increased expenditure on protective products.

Local governments are required to implement the National "12$^{\text{th}}$ Five-Year Plan" for Environmental Protection and assign its objectives and tasks to specific local cities and firms for execution. While the automatic monitoring system enhances pollution data quality and benefits the environment (Greenstone et al. (2021)), polluting firms are likely to face heightened scrutiny from local governments regarding their environmental performance. Choi et al. (2025) find that stock prices of less sustainable companies fell more than those of sustainable companies after the monitoring system was introduced, indicating that the market expects a larger negative effect on polluting firms.

With increased regulatory oversight and negative public perception, we hypothesize that polluting firms are motivated to engage in dishonest practices in the governance dimension, such as earnings management. Our hypothesis is consistent with the argument made by Zang (2012), who shows that real activities manipulation and accrual-based earnings management serve as substitutes in a broader context. The automatic monitoring system raises the costs of manipulating air pollutant data, which may increase the chance that firms engage in earnings management. The direction of earnings management depends on the pressures a company faces. Since the government might focus on larger and more profitable firms, polluting companies have an incentive to manage earnings downward to avoid attracting regulatory scrutiny and to meet public expectations for reducing pollution. On the other hand, polluting firms might inflate their profits to reassure stakeholders and show financial strength, leading to upward earnings management.

We use discretionary accruals (Dechow et al. (1995); Jones (1991)) to capture the magnitude and direction of accrual-based earnings management and conduct a standard difference-in-differences (DiD) analysis around the policy change in 2012.[3] The polluting industries are defined in *The Directory of Classified Management of Environmental Protection Verification* issued by the MEE in 2008; the list contains 16 categories of industries, including thermal power, steel, cement, electrolytic aluminum, coal, and metallurgy. We find that following the announcement of the new monitoring system, polluting firms increase the magnitude of the absolute discretionary accruals by 1.63% and raise the probability of a negative adjustment in discretionary accruals by 10.4% relative to other industries, consistent with our hypothesis that polluting firms prefer to stay "low-key" and avoid drawing undesired attention of the government by managing earnings.

Polluting and non-polluting industries exhibit insignificant differences in discretionary accruals prior to 2012, justifying the parallel-trend assumption. We also find that the earnings management activity lasts for at least three years after the policy change, as polluting firms might continue to face regulatory scrutiny after 2012. We then use corporate headquarters locations to perform additional tests. The automatic monitoring system was implemented in different cities in three waves between 2012 and 2014. In three separate DiD estimations, a firm is considered treated after its headquarters city has implemented the monitoring system. The results from these three DiD estimations yield similar results, as shown by an increase in polluting firms' absolute discretionary accruals by 1.57% in the first wave, 1.26% in the second wave, and 2.94% in the third wave. The sequential launch of the monitoring system increases the probability of a negative adjustment in discretionary accruals for polluting firms by 8.27%, 13.8%, and 8.66% in the first, second, and third waves, respectively.

In addition, we explore the possibility that polluting firms are instead deploying discretionary accruals to strategically convey negative private information to other stakeholders.

[3]One caveat is that we do not directly observe managers' dishonest earnings distortion behavior. We follow the accounting literature and use discretionary accruals as a proxy for accrual-based earnings management, a technique adopted by companies to manipulate their financial statements by adjusting accruals. Discretionary accruals are the difference between firms' actual accruals and the normal level of accruals; the latter is estimated using the modified Jones (1991) model. As Kothari et al. (2005) point out, this type of tests are joint tests of the researcher's model of discretionary accruals and earnings management. In our context, the model misspecification concern is mitigated because our difference-in-differences approach focuses on the discretionary accruals related to the event of interest.

We examine the long-window earnings response coefficients (ERC). If managers strategically convey negative private information, the long-window ERC should be greater for polluting firms following the policy change. Our results, however, indicate a drop in the long-window ERC for polluting industries, relative to non-polluting firms, after the announcement of the automatic monitoring system. It appears that polluting firms are not adjusting their earnings to convey truly negative private information but are managing financial reporting to show lower earnings.

Then we study the impact of the environmental policy on earnings management conditional on the exposure to regulatory risks. Watts and Zimmerman (1978) suggest that larger and more profitable firms are more susceptible to "political costs," as regulators often see them as prime targets. It may be easier for the government to convey to the public that profits should not come at the expense of people's health by focusing on lucrative polluting companies. If polluting firms manage earnings to evade regulatory scrutiny, the political costs of firms should exacerbate this behavior. Following the argument by Watts and Zimmerman (1978), we use firm size and profitability growth to capture a firm's visibility and, consequently, its regulatory risks. We find that polluting firms with greater total assets and higher growth in profitability have more significant changes in the magnitude of earnings management.

In addition, we assess the regulatory risks based on the extent of government intervention in corporate businesses. First, we use the proximity of a firm's headquarters to the monitoring stations. Yang et al. (2024) show that areas close to automated monitors experience a 3.2% decrease in $PM_{2.5}$ concentrations relative to those farther away. They find evidence that local governments implement more action plans near the monitors. Consistent with these findings, we show that earnings management is more pronounced if the polluting firm's headquarters is within a 3-km radius of a monitoring station. Then we use the province-level marketization index as a measure (Fan et al. (2011)), assuming that local governments are more likely to intervene in less market-oriented regions. We observe that polluting firms engage more in earnings management in regions with lower levels of marketization.

Finally, we examine situations in which firms' incentives to manage earnings vary due to their relationships with other firms. The literature suggests that customer-supplier relationships have an impact on earnings management. For example, Kim and Luo (2022) propose the monitoring and certifying roles that large customers can play in reducing corporate earnings management activities; Raman and Shahrur (2008) argue that firms tend to reduce their earnings management practices due to the monitoring by their suppliers. Consistent with these findings, we show that polluting firms with a more concentrated major customer base do not significantly change their earnings management behavior after the policy change. We measure the strength of the connection between firms and their suppliers through trade credit, and our findings reveal that post-policy earnings management is attenuated among polluting firms with more robust connections with their upstream suppliers. Finally, since extensive prior research (e.g, Verrecchia (1983), Darrough (1993), Fan and Wong (2002)) indicates that firms may conceal their activities from competitors by providing less informative disclosures, we examine how earnings management varies with market competition. We find that market competition exacerbates polluting firms' earnings management following the policy change. These results suggest that polluting firms are more likely to manage earnings post-monitoring reform if the potential benefits are higher and the costs are lower.

Our paper makes two primary contributions. First, we add to the growing literature on ESG by showing the conflict within the three pillars. While high sustainability firms usually are more long-term oriented and have better ESG practices (Eccles et al. (2014)), our findings reveal that firms may prioritize short-term governance goals at the expense of long-term environmental and social responsibilities. The case of Volkswagen illustrates how a focus on appearing environmentally friendly can lead to unethical practices, such as data manipulation. Our research provides more systematic evidence that polluting firms, under pressure to meet regulatory and public expectations, may engage in dishonest behavior related to earnings management. While Deng et al. (2020) argue that investors may be able to discern "greenwashing" in China, a conflict between E and G is perhaps less obvious.

Second, we explore the unintended consequences stemming from environmental policy changes. While the automatic air pollutant monitoring system in China was designed to enhance transparency and improve air quality, our research indicates that it inadvertently incentivizes polluting firms to engage in earnings management. Our results point to a strategic response by polluting firms to minimize regulatory attention. This finding underscores the complexity of environmental regulations, as well-intentioned policies can create perverse incentives that undermine their effectiveness. The design and implementation of future environmental regulations should also consider social and governance factors to enhance overall welfare.

The remainder of the paper is structured as follows. Section 2 briefly describes the background of the automatic monitoring system. In Section 3, we list the data sources. Sections 4 and 5 present the main results and cross-sectional results. Section 6 concludes.

2 Policy Background

Over the past few decades, the Chinese government has launched extensive environmental regulatory reforms across various sectors to promote a greener economy. A key element of this effort was the introduction of the Ambient Air Quality Standards (GB 3095-2012) and the establishment of a real-time pollutant reporting and monitoring system in 2012. The automated air pollutant monitoring system plays a crucial role in China's anti-pollution campaign by enabling immediate data transmission from monitoring equipment to both the central government and the public. This transparency significantly reduces the chance that local governments manipulate air quality data.

In 2012, the Ministry of Environmental Protection, the National Development and Reform Commission, and the Ministry of Finance mandated that local governments diligently implement the National "12th Five-Year Plan" for Environmental Protection. The plan emphasizes the crucial role of local governments in implementing environmental policies. Local authorities are tasked with integrating the plan's targets and measures into their economic and social development strategies. They are responsible for monitoring local firms, ensuring compliance with environmental standards, and addressing pollution issues effectively. Local governments would conduct regular assessments of firms' environmental performance, particularly focusing on those that discharge significant pollutants. As a result, local polluting companies face increased pressure to comply with environmental regulations.[4] In July 2012, the Ministry of Environmental Protection introduced Environmental Inspection Measures. These measures mandate that environmental inspectors carry out on-site inspections and enforce legislation. We hypothesize that larger and more profitable firms are more susceptible to political costs, as these firms are more likely to be targeted by regulators.

Several other papers also examine how political costs affect earnings management. Cahan et al. (1997) show that chemical firms with higher political costs are more likely to engage in income-decreasing accruals at the height of Congress's debate over the passage of the Comprehensive Environmental Response, Compensation, and Recovery Act of 1980. This law allowed the U.S. Government to clean up hazardous chemical waste sites and created a Superfund, mainly financed by the chemical industry, to pay for the cleanup expenses. Han and Wang (1998) report that oil companies use accruals to reduce earnings during the 1990 Persian Gulf Crisis, as these companies seek to lower political sensitivity amid sudden product price increases. Patten and Trompeter (2003) find that U.S. chemical firms exhibit significant negative discretionary accruals after the chemical leak at Union Carbide's India plant in December 1984. The accident sparked worries that congressional investigations might result in stricter regulations, which could significantly raise costs for chemical com-

[4]See *Circular of the State Council on Printing Out and Distribution of the National "12th Five-Year Plan" for Environmental Protection*, available at `https://english.mee.gov.cn/Resources/Plans/National_Fiveyear_Plan/201606/P020160601356854927248.pdf`. The Circular states that enterprises are responsible for environmental protection and can face penalties if they violate environmental regulations—"Any enterprise with high environmental risk will be set down on the blacklist for supervision, requested to remedy or be relocated within a given period of time, or even shut down according to law if it does not meet the conditions for remedy."

panies. Because of this, management might have been motivated to present themselves as financially vulnerable by reporting lower earnings. Our paper differs from these studies in that the policy we examine has created an incentive for typical polluting firms to manage earnings. Political costs and competition exacerbate this behavior, while discipline from customers and suppliers mitigates it.

3 Data

The financial and accounting information is obtained from the China Stock Market and Accounting Research Database (CSMAR). The categorization of polluting industries and the list of cities required to implement the new technology are collected from the Ministry of Environmental Protection website in 2008.[5] The province-level marketization index is downloaded from China's National Economic Research Institute platform. We include in the sample all non-financial and non-special-treated firms listed in the Shenzhen Stock Exchange and Shanghai Stock Exchange with relevant required data.[6] The sample period spans from 2009 to 2014, focusing on the announcement of the forthcoming launch of the automatic monitoring system. We require non-missing financial information for an observation to be included. Our sample contains 11,040 unique firm-year observations from 759 polluting firms and 1,696 non-polluting firms for the regression with $|DA|$, the absolute value of discretionary accruals, as the dependent variable. The regression with $BHAR$, buy-and-hold abnormal returns, contains 9,858 unique firm-year observations from 752 polluting firms and 1,659

[5] The pollution industries and their industry codes are: Coal mining and washing industry (B06); Oil and gas extraction industry (B07); Ferrous metal mining and dressing industry (B08); Nonferrous metal mining and dressing industry (B09); Textile industry (C17); Leather, fur and feather (cashmere and products industry) (C19); Paper making and paper products industry (C22); Petroleum processing, coking and nuclear fuel processing industry (C25); Chemical fuel and chemical products manufacturing (C26); Pharmaceutical manufacturing industry (C27); Chemical fiber manufacturing (C28); Rubber products industry (C29); Plastic products industry (C30); Non-metallic mineral products industry (C31); Ferrous metal smelting and rolling processing industry (C32); Power and heat production and supply industries (D44).

[6] The Shanghai and Shenzhen Stock Exchanges in China provide special treatment or delisting risk warnings for stocks of listed companies facing unusual financial situations or other irregular conditions, aimed at informing investors about the associated risks. Given these abnormal conditions, we remove specially treated firms from our analysis.

non-polluting firms. Data on the monitoring stations' locations are collected from the Hong Kong University of Science and Technology Atmospheric & Environmental Database, which covers 1,045 stations from 2010 to 2014.

4 Main Results

To examine earnings management, we calculate discretionary accruals from the Modified Jones model (DA, Dechow et al. (1995); Jones (1991)) as follows:

$$\frac{TA_{i,t}}{A_{i,t-1}} = \beta_1 \frac{1}{A_{i,t-1}} + \beta_2 \frac{\Delta REV_{i,t} - \Delta REC_{i,t}}{A_{i,t-1}} + \beta_3 \frac{PPE_{i,t}}{A_{i,t-1}} + \varepsilon_{i,t} \tag{1}$$

$$DA_{i,t} = \frac{TA_{i,t}}{A_{i,t-1}} - \hat{\beta}_1 \frac{1}{A_{i,t-1}} - \hat{\beta}_2 \frac{\Delta REV_{i,t} - \Delta REC_{i,t}}{A_{i,t-1}} - \hat{\beta}_3 \frac{PPE_{i,t}}{A_{i,t-1}}, \tag{2}$$

where $TA_{i,t}$ denotes the total accruals, defined as the operating income minus operating cash flows; $A_{i,t-1}$ is the lagged total assets; $\Delta REV_{i,t}$ is the change in revenue from year $t-1$ to year t; $\Delta REC_{i,t}$ is the change in account receivables from year $t-1$ to year t; and $PPE_{i,t}$ is property, plant, and equipment. The coefficients in Equation (1) are estimated cross-sectionally for industry-year groups with at least 10 observations. Equation (2) calculates the residual of regression Equation (1); $DA_{i,t}$ is the discretionary accruals, defined as the difference between firms' actual accruals and the normal level of accruals, serving as a proxy for earnings management. CSMAR runs Equations (1) and (2) and provides estimates of $DA_{i,t}$.

We evaluate the impact of the environmental policy on earnings management by estimating a standard Difference-in-differences model:

$$|DA|_{i,t} = \beta_1 AMS_t \times Pollute_i + \beta_2 Controls_{i,t} + \beta_3 Pollute_i + \varepsilon_{i,t}, \tag{3}$$

where $|DA|_{i,t}$ is the absolute value of $DA_{i,t}$. A positive (negative) $DA_{i,t}$ suggests that firm

i has made income increasing (decreasing) accrual adjustments in year t, which suggests positive (negative) earnings management.

Control variables in Equation (3) include the natural logarithm of total assets (*Size*), the debt-to-asset ratio (*Lev*), the return on assets (*ROA*), and an indicator variable of negative net income (*Loss*). To control for the impact of corporate governance on accounting strategy, we also include the natural logarithm of the number of directors (*Board*), the percentage of independent directors in the board (*Indep*), an indicator variable of whether the CEO is the same person as the chairman of the board (*Dual*), the percentage of shares held by the largest shareholder (*Top1*), the percentage of shares held by the largest five shareholders (*Top5*), an indicator variable of whether a firm has a big four auditor (*Big 4*), an indicator variable of whether the firm has received an unqualified opinion (*Opinion*), and an indicator variable of whether the firm is a state-owned enterprise (*SOE*). Year and province fixed-effects are included. Standard errors are clustered by firm.

The variable of interest is $AMS_t \times Pollute_i$, which equals one for the observations of polluting firms in the years following the announcement of the monitoring system. As the Ministry of Environmental Protection in China announced the Ambient Air Quality Standards (GB 3095-2012) and a nationwide implementation plan in February 2012, AMS_t equals one from 2012 onward, and zero otherwise. $Pollute_i$ equals one if the firm belongs to one of the polluting industries, defined by *the Directory of Classified Management of Environmental Protection Verification* issued by the Ministry of Environmental Protection in 2008.

Table 1 displays the summary statistics. The mean $|DA|$ is 0.078, indicating that the magnitude of discretionary total accruals is 7.8% of total assets. As shown by the mean of AMS, the announcement of the monitoring system affects 17.9% of our sample observations. Before showing the results of Equation (3), it is helpful to discuss an alternative hypothesis. The introduction of the automatic monitoring system may help curb unethical business practices instead. For example, government inspection may be a deterrent to the misreporting behavior of polluting firms. It may either improve or, at the very least, not lead to a decline in the quality of earnings.

In Columns (1) and (2) of Table 2, we present the main result on the impact of the announcement on firms' absolute discretionary accruals ($|DA|_{i,t}$). The coefficient on $AMS_t \times Pollute_i$ is positive and significant at the 1% level, suggesting that polluting firms engage more in earnings management and their earnings quality goes down after the announcement. In terms of the economic magnitude, absolute discretionary accruals of polluting firms increase by about 1.7%, relative to non-polluting firms, from the pre- to the post-monitoring period. Given that the mean of absolute discretionary accruals is 7.8%, the results are both statistically and economically significant. This finding is inconsistent with the alternative hypothesis that the environmental policy deters financial misreporting.

The estimated coefficient on the variable $AMS_t \times Pollute_i$ is the average difference in the changes of earnings quality of polluting firms and non-polluting firms from pre- to post-announcement of the new standards, regardless of whether the monitoring system in the firms' located city has been launched or not. According to the implementation schedule, the monitoring equipment was introduced in different cities sequentially in three waves, so we also run three separate regressions, in which the variable $AMS_t \times Pollute_i$ is replaced by a treatment variable $LMS_t \times Pollute_i$ (L stands for local) that equals one in years when the city where the polluting firm is located has launched the monitoring system, and zero otherwise.

As stated in the *Timeline for the Implementation of New Standards*, the Beijing–Tianjin–Hebei mega-city region, the Yangtze River Delta, the Pearl River Delta, as well as municipalities and provincial capital cities are required to complete the system enhancement by the end of 2012 in the first wave. Hence, LMS_t equals one for firms located in these regions starting from 2012, while for firms in the regions of 113 critical environmental protection and national model cities under the second wave of the implementation scheme, LMS_t turns from zero to one starting from 2013, and from 2014 for all the remaining polluting firms located in cities at the prefecture level or above.[7] The results from Columns (3)–(5) of Table 2 show that the three separate DiD estimations yield similar results—polluting firms' absolute discretionary accruals increase by 1.57% in the first wave, 1.26% in the second wave, and 2.94% in the third wave, relative to non-polluting firms.

To assess whether the assumption behind the DiD estimation holds, that is, the parallel trend assumption, we construct a dynamic model that includes the interactions between $Pollute_i$ and time variables AMS_{t-2}, AMS_{t-1}, AMS_t, AMS_{t+1}, AMS_{t+2}, and AMS_{t+3}, which equal one for firms in the corresponding year relative to 2012, the year that new environmental standards are required to implement, and zero otherwise. Thus, $AMS_{t-2} \times Pollute_i$ and $AMS_{t-1} \times Pollute_i$ measure the difference in earnings quality between polluting and non-polluting firms in the two years before the announcement of new standards. The null hypothesis of the non-existence of a pre-determined trend implies that coefficients on $AMS_{t-2} \times Pollute_i$ and $AMS_{t-1} \times Pollute_i$ should be statistically insignificant (Bertrand and Mullainathan (2003)). In Column (6), we report the results of the dynamic effects model. Consistent with the parallel-trend assumption, coefficients on $AMS_{t-2} \times Pollute_i$ and $AMS_{t-1} \times Pollute_i$ are statistically indistinguishable from zero. In contrast, the coefficients on $AMS_t \times Pollute_i$, $AMS_{t+1} \times Pollute_i$, $AMS_{t+2} \times Pollute_i$, and $AMS_{t+3} \times Pollute_i$ are significantly positive, implying that polluting firms engage in more earnings management activities immediately after the announcement of air quality monitoring system and that this impact lasts for at least three years.[8]

We then examine the direction of the earnings management. On the one hand, polluting firms may adopt a "play-it-safe" strategy and engage in downward earnings management as a precautionary measure to avoid becoming the target of the government's emission reduction campaign and to align with the public's expectation of scaling down the polluting industries. On the other hand, polluting companies may hide their losses and exaggerate profits to

[7] See Greenstone et al. (2022) for the full list of cities and the implementation dates. In our tests, polluting firms treated in a previous wave are excluded from the analysis of subsequent waves.

[8] The central government carried out a final evaluation of overall pollution reduction in 2017, as stated in the Air Pollution Prevention and Control Action Plan released in 2013.

avoid alarming stakeholders such as creditors, customers, and suppliers, making it possible for managers to engage in upward earnings management to pursue private benefits under performance pressure. For example, Healy (1985) and Holthausen et al. (1995) demonstrate that managers manipulate earnings to meet performance targets tied to bonus compensation, and Guan et al. (2005) indicate that managers inflate earnings to ensure job security.

Table 3 shows the results of regressing an indicator of whether $DA_{i,t}$ is negative on the treatment and control variables using OLS and logistic models. The coefficients in Column (1) suggest that the announcement of the monitoring system increases the probability (log odds) of downward earnings management for polluting firms by about 10.40% (46.1%), relative to non-polluting firms. In Columns (3)–(6), the effects of implementing the monitoring system on the probability (log odds) of downward earnings management for polluting firms are 8.27% (35.5%),13.8% (61.6%), and 8.66% (40.9%), for the first, second, and third wave, respectively, relative to non-polluting firms. The results are in favor of downward earnings management.

After examining the changes in the quality of earnings, we study the change in the informativeness of reported earnings. Here we attempt to rule out an alternative hypothesis that firms manage earnings downward to convey managers' private information about poor performance forecasts (e.g., Watts (1986), Subramanyam (1996) and Guay et al. (1996)). In anticipation of a decline in earnings, managers may manage earnings conservatively to convey the economic shock that has not yet been reflected in the current-period income statement. Chaney and Jeter (1992) suggest that long-window earnings response coefficients (ERC) can serve as a measure of earnings informativeness. A larger long-window ERC indicates that a broader range of information is available to market participants, allowing them to more effectively interpret the financial statements. Therefore, we estimate the following earnings-return relationship with year and industry fixed effects.

$$\begin{aligned} BHAR_{i,t} = & \beta_1 UE_{i,t} + \beta_2 UE_{i,t} \times AMS_t + \beta_3 UE_{i,t} \times Pollute_i \\ & + \beta_4 AMS_t \times Pollute_i + \gamma_5 UE_{i,t} \times AMS_t \times Pollute_i + \varepsilon_{i,t}, \end{aligned} \tag{4}$$

$$BHAR_{i,t} = \prod_{m=1}^{12}(1 + R_{i,m}) - \prod_{m=1}^{12}(1 + R_{b,m}). \tag{5}$$

$BHAR_{i,t}$ is the 12-month buy-and-hold stock abnormal returns from May of one year to April of the following year, calculated based on the monthly stock return rates considering cash dividends reinvested minus the benchmark returns (Equation (5)). This time alignment considers the disclosure of annual financial reports released by the end of April of the following year. $UE_{i,t}$ is the unexpected earnings, calculated as the change in earnings per share (EPS) from the previous year scaled by the stock price at the beginning of year t. $Pollute_i$ is an indicator variable that equals one if firm i is in the polluting industries and zero otherwise. AMS_t is an indicator variable that equals one if the year is 2012 or later for firm i in period t, and zero otherwise. The coefficient on the variable $UE_{i,t}$ is the earnings response coefficient for non-polluting firms before 2012, and the coefficient on the variable $UE_{i,t} \times AMS_t \times Pollute_i$ captures the effect of implementing new environmental standards on polluting firms' earnings response coefficient.

Table 4 presents the estimated results of Equation (4). The benchmark returns are equal-weighted, free float value-weighted, and total market value-weighted market returns in Columns (1)–(3). The coefficients on the interaction term $UE_{i,t} \times AMS_t \times Pollute_i$ are all negative and statistically significant at the 1% level. This finding suggests a drop of 0.62 to 0.64 in the long-window ERC for polluting industries than non-polluting industries in the aftermath of the monitoring equipment automation campaign. The results do not align with the hypothesis that polluting firms deploy downward management to convey insightful private information about future performance, but rather suggest that the earnings of polluting firms contain more noisy signals than non-polluting ones following the announcement of the air quality monitoring system.

5 Cross-sectional Analysis

The evidence thus far suggests that polluting firms engage in downward earnings management, which worsens the quality of information content in financial reports. We conjecture that polluting firms respond to the regulatory pressure by concealing profits. To further support this hypothesis, we examine how the impact of the launch of an air quality monitoring system on earnings quality varies with firms' exposure to regulatory risk and, hence, the political costs. Watts and Zimmerman (1978) suggest that political costs arise when firms become targets of political attention and potential regulation, and these costs include increased taxes, government scrutiny, and other regulatory actions and can be a significant factor influencing the determination of accounting standards. As Watts and Zimmerman (1978) suggested, larger and more profitable firms are more vulnerable to governmental wealth transfers as regulators often view them as significant targets.

First, we split the sample based on total assets and the change in profit growth and estimate the effects of the policy change on earnings quality using the subsamples. The results in Panel A of Table 5 are consistent with the political cost hypothesis as the coefficients on $AMS_t \times Pollute_i$ are about 2.61% for the sample of larger firms and only 0.89% for the sample of smaller firms. Panel B shows that polluting firms that experience higher growth in profitability in 2011 exhibit a more considerable decline in their earnings quality than their under-performing peers; the magnitude of coefficients on DA of the high growth group (3.19%) is more than twice that of the low growth group (1.27%).

Next, we estimate a firm's regulatory risks based on its headquarters' location. Yang et al. (2024) demonstrate that regions near automated monitors see a 3.2% reduction in $PM_{2.5}$ concentrations compared to areas that are farther away. The authors review government documents and identify some that mention "atmospheric pollution control around monitoring stations" and specify detailed pollution control measures to be implemented around the monitoring stations. These measures include regulations on coal usage, dust suppression via water spraying, traffic restrictions, bans on open burning and outdoor cooking, and the closure of major polluting plants. Therefore, we believe that a firm's regulatory risks are higher if it is located near a monitoring station. In Panel A of Table 6, we show that the results among firms located within a 3km-radius of a monitoring station are indeed stronger than those located farther away.

We also use the Fan Gang Marketization Index (Fan et al. (2011)) to measure the likelihood of government intervention in corporate businesses. We expect the monitoring system's impact to be more salient in less economically developed (i.e., more intervened) markets. Consistent with our expectation, we find in Panel B that the results are more pronounced in the subsample of less developed regions. The magnitude of coefficients there is almost twice that of more developed regions, suggesting that the earnings management effect is stronger among polluting firms that run businesses with more regulatory risks.

After identifying the mechanism underlying our key findings, we explore the variation in firms' relationships with other stakeholders and firms. Examining how the relationship with upstream and downstream stakeholders influences the impact of environmental regulatory change on earnings management enables us to consider how firms' strategic behavior is shaped based on the trade-off between the benefits of downward earnings management and the obligation to meet stakeholders' expectations and maintain their relationship. Regarding customers, Panel A of Table 7 finds no evidence that polluting firms with a concentrated major customer base change their earnings management behavior. Monitoring by major customers or customer concentration risk appears to be a disciplinary role and restricts polluting firms' manipulation in financial reporting.

In Panel B, we measure the strength of the connection between firms and their suppliers through trade credit, and our findings reveal that the effect on earnings management is attenuated among polluting firms with more robust connections with their upstream suppliers, implying that firms may restrain their downward earnings management motives to avoid undermining their creditors' confidence. Finally, since prior research documents that firms tend to hide their actual financial positions from competitors, we examine how the earnings management effect varies with market competition in Panel C. We find that market competition exacerbates polluting firms' earnings management behavior, as polluting firms operating in competitive industries manage their earnings to a greater extent following the regulatory change.

6 Conclusion

The establishment of a pollution monitoring system is crucial to the success of China's "War on Pollution." Understanding potential unintended consequences can help assess the benefits and costs of this important policy. The goal of environmental monitoring technology is to improve long-term social welfare. However, in the short term, firms may manage earnings due to pressure from government intervention. Our research shows that polluting firms significantly adjust discretionary accruals downward in the post-monitoring period compared to non-polluting firms, negatively impacting the quality of financial reports. Firms facing greater regulatory risks respond more dramatically. Furthermore, those reliant on upstream and downstream partners are less likely to manage earnings, while market competition tends to exacerbate this behavior.

This paper contributes to the broader discussion of corporate governance and sustainability, providing insights into how companies balance economic and environmental compliance. By highlighting the unintended financial distortions caused by environmental regulations, we aim to inform policymakers, regulators, and scholars about the complex relationship between environmental and governance issues.[9] Several developing countries, including Brazil and Mexico, have recognized the importance of air quality monitoring and invested in in-

[9] Kruger (2015) shows that investors in U.S. firms react strongly negatively to negative Corporate Social Responsibility (CSR) events and weakly negatively to positive events. It will also be interesting to see how investors react to news that increases one dimension of ESG but decreases another.

frastructure to address environmental and public health issues, providing public access to air quality data to encourage community involvement.[10] While many companies in developing countries are state-owned, which are more responsive to environmental issues (as shown by Hsu et al. (2023)), our findings suggest that the public disclosure of environmental information can create pressure on firms. Policymakers should consider the potential negative impacts on other welfare dimensions when enhancing environmental information monitoring technology.

[10]In Brazil, The Institute of Energy and Environment (IEMA) developed the Air Quality Platform in 2015 to promote the transparency of air quality information. Sistema de Monitoreo Atmosférico (SIMAT) in Mexico has established more than 40 monitoring stations to inform the population about real-time pollution levels.

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Table 1: Summary Statistics

This table reports descriptive statistics for our measures of earnings management, control variables, and buy-and-hold abnormal returns for the sample used in the regression analysis. The sample covers the period 2009-2014 and contains 11,040 (9,858) unique firm-year observations from 759 (752) polluting firms and 1,696 (1,659) non-polluting firms for the regression with $|DA|$(BHAR) as the dependent variable. $|DA|$ is the absolute value of discretionary accruals and is constructed using the Modified Jones model. *Size* is the natural logarithm of total assets, *Lev* is the debt-to-asset ratio, *ROA* is the return on assets, *Loss* is an indicator variable of negative net income, *Board* is the natural logarithm of the number of directors, *Indep* is the percentage of independent directors in the board, *Dual* is an indicator variable of whether the CEO is the same person as the chairman of the board, *Top1* is the percentage of shares held by the largest shareholder, *Top5* is the percentage of shares held by the largest five shareholders, *Big 4* is an indicator variable of whether a firm has a big four auditor, *Opinion* is an indicator variable of whether the firm has received an unqualified opinion, and *SOE* is an indicator variable of whether the firm is a state-owned enterprise. UE is the unexpected earnings, calculated as the change in earnings per share (EPS) from the last year scaled by the stock price at the beginning of the year. *Pollute* is an indicator variable that equals one for firms in the polluting industries and zero otherwise.

Variable	Obs	Mean	Std. Dev.	Min	Max
$\|DA\|$	11040	0.078	0.100	0.000	3.261
$DA < 0$	11040	0.354	0.478	0.000	1.000
Size	11040	21.945	1.296	15.577	28.509
Lev	11040	0.453	0.218	0.007	2.529
ROA	11040	0.043	0.061	-0.999	0.517
Loss	11040	0.087	0.282	0.000	1.000
Indep	11040	0.370	0.055	0.000	0.800
Dual	11040	0.224	0.417	0.000	1.000
Board	11040	2.168	0.200	1.386	2.890
Top1	11040	0.363	0.156	0.022	0.894
Top5	11040	0.528	0.162	0.030	0.981
Big4	11040	0.059	0.235	0.000	1.000
Opinion	11040	0.975	0.155	0.000	1.000
SOE	11040	0.466	0.499	0.000	1.000
UE	9858	0.004	0.066	-1.885	1.201
Pollute	9858	0.314	0.464	0.000	1.000
BHAR-EW	9858	-0.067	0.511	-1.757	15.812
BHAR-FVW	9858	0.059	0.511	-1.437	16.144
BHAR-TVW	9858	0.064	0.513	-1.490	16.080

Table 2: Air Quality Monitoring and Earnings Management: Magnitude

This table reports the results of OLS regressions examining the effect of the introduction of the air quality monitoring system on the magnitude of firms' earnings management. Our sample contains 759 polluting firms and 1,696 non-polluting firms. The dependent variable is the absolute discretionary accruals. $AMS_{i,t}$ is an indicator variable that equals one for the observations in the years following the announcement of the monitoring system. $LMS_{i,t}$ is an indicator variable that equals one in years when the city where the firm is located has launched the monitoring system. Definitions for other variables can be found in Table 1. Columns 1, 2, and 6 use the full sample, and Columns 3–5 use the samples that include non-polluting firms and polluting firms located in regions where the monitoring system was launched in the first, second, and third waves, respectively. T-statistics, shown in parentheses, are computed based on standard errors clustered by firms. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
Sample			First	Second	Third	
Dependent Variable	$\|DA\|$	$\|DA\|$	$\|DA\|$	$\|DA\|$	$\|DA\|$	$\|DA\|$
AMS_t × Pollute	0.0169***	0.0163***				0.0182***
	(4.250)	(4.176)				(2.712)
LMS × Pollute			0.0157***	0.0126**	0.0294**	
			(3.669)	(2.211)	(2.111)	
AMS_{t-2} × Pollute						0.000642
						(0.0907)
AMS_{t-1} × Pollute						0.0121
						(1.592)
AMS_{t+1} × Pollute						0.0199***
						(2.852)
AMS_{t+2} × Pollute						0.0250***
						(3.447)
Size		-0.00274**	-0.00322**	-0.00242	-0.00195	-0.00273**
		(-2.096)	(-2.245)	(-1.525)	(-1.170)	(-2.091)
Lev		0.0730***	0.0812***	0.0872***	0.0876***	0.0729***
		(9.362)	(9.483)	(9.213)	(8.998)	(9.347)
ROA		0.141***	0.123***	0.182***	0.129**	0.141***
		(3.241)	(2.660)	(3.326)	(2.340)	(3.238)
Loss		0.0118***	0.00883**	0.0142***	0.00840	0.0117***
		(2.904)	(2.022)	(2.841)	(1.639)	(2.894)
Indep		-0.0185	-0.0139	-0.0224	-0.0324	-0.0187
		(-0.924)	(-0.635)	(-0.947)	(-1.331)	(-0.936)
Dual		-0.000359	-0.00166	-0.00299	-0.00190	-0.000338
		(-0.132)	(-0.566)	(-0.937)	(-0.568)	(-0.124)
Board		-0.0243***	-0.0291***	-0.0283***	-0.0324***	-0.0243***
		(-3.631)	(-3.806)	(-3.604)	(-3.878)	(-3.632)
Top1		-0.000144	-0.00655	0.00454	0.00166	-0.000192
		(-0.0104)	(-0.426)	(0.269)	(0.0963)	(-0.0139)
Top5		0.0291**	0.0382***	0.0377**	0.0384**	0.0291**
		(2.346)	(2.754)	(2.434)	(2.418)	(2.345)
Big4		-0.0162***	-0.0181***	-0.0237***	-0.0254***	-0.0161***
		(-3.669)	(-3.787)	(-4.347)	(-4.755)	(-3.650)
Opinion		-0.0169**	-0.0143*	-0.0131*	-0.00967	-0.0170**
		(-2.529)	(-1.912)	(-1.696)	(-1.239)	(-2.535)
SOE		-0.0154***	-0.0164***	-0.0164***	-0.0176***	-0.0154***
		(-5.407)	(-5.214)	(-4.996)	(-5.130)	(-5.403)
Pollute	-0.0144***	-0.0121***	-0.0166***	0.000822	-0.00174	-0.0169***
	(-3.931)	(-3.380)	(-4.134)	(0.185)	(-0.355)	(-2.693)
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Province FE	Yes	Yes	Yes	Yes	Yes	Yes
Cluster by Firm	Yes	Yes	Yes	Yes	Yes	Yes
Observations	11,040	11,040	9,547	8,481	8,232	11,040
R^2	0.019	0.043	0.048	0.051	0.050	0.043

Table 3: Air Quality Monitoring and Earnings Management: Direction

This table reports the results of OLS and logistic regressions examining the effect of the introduction of the air quality monitoring system on the direction of firms' earnings management. Our sample contains 759 polluting firms and 1,696 non-polluting firms. Columns 1 and 2 use the full sample, and Columns 3–8 use the samples that include non-polluting firms and polluting firms located in regions where the monitoring system was launched in the first, second, and third waves. The dependent variable indicates whether $|DA|$ is negative. Definitions for other variables can be found in Table 1. T-statistics, shown in parentheses, are computed based on standard errors clustered by firms. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Sample			First Wave		Second Wave		Third Wave	
Model	OLS	Logit	OLS	Logit	OLS	Logit	OLS	Logit
Dependent Variable	$DA < 0$	$DA < 0$	$DA < 0$	$DA < 0$	$DA < 0$	$DA < 0$	$DA < 0$	$DA < 0$
AMS × Pollute	0.104***	0.461***						
	(5.408)	(5.056)						
LMS × Pollute			0.0827***	0.355***	0.138***	0.616***	0.0866*	0.409*
			(3.452)	(3.190)	(4.124)	(4.041)	(1.794)	(1.898)
Size	-0.0172***	-0.0800***	-0.0192***	-0.0897***	-0.0226***	-0.107***	-0.0256***	-0.121***
	(-2.918)	(-2.874)	(-2.978)	(-2.922)	(-3.380)	(-3.347)	(-3.682)	(-3.602)
Lev	0.183***	0.823***	0.184***	0.838***	0.182***	0.839***	0.188***	0.870***
	(5.916)	(5.527)	(5.469)	(5.152)	(5.300)	(5.026)	(5.329)	(5.063)
ROA	-1.067***	-6.254***	-1.064***	-6.222***	-1.004***	-5.959***	-0.975***	-5.731***
	(-10.35)	(-9.321)	(-8.950)	(-8.212)	(-8.259)	(-7.681)	(-7.823)	(-7.255)
Loss	0.110***	0.324***	0.118***	0.366***	0.115***	0.342***	0.117***	0.361***
	(5.433)	(3.388)	(5.210)	(3.410)	(4.786)	(3.025)	(4.637)	(3.070)
Indep	-0.0849	-0.408	-0.116	-0.568	-0.0393	-0.193	-0.0762	-0.373
	(-0.885)	(-0.890)	(-1.128)	(-1.144)	(-0.358)	(-0.361)	(-0.686)	(-0.686)
Dual	0.000778	0.00240	-0.00172	-0.00792	-0.00200	-0.0119	-0.0108	-0.0531
	(0.0647)	(0.0414)	(-0.135)	(-0.127)	(-0.150)	(-0.182)	(-0.796)	(-0.788)
Board	-0.0318	-0.150	-0.0205	-0.0976	-0.0318	-0.151	-0.0202	-0.0894
	(-1.091)	(-1.093)	(-0.658)	(-0.657)	(-0.958)	(-0.947)	(-0.605)	(-0.554)
Top1	-0.0167	-0.0923	-0.0432	-0.215	-0.0678	-0.349	-0.0434	-0.225
	(-0.325)	(-0.373)	(-0.769)	(-0.792)	(-1.139)	(-1.198)	(-0.716)	(-0.750)
Top5	-0.0248	-0.0873	-0.0193	-0.0657	-0.00604	0.00734	-0.0462	-0.191
	(-0.507)	(-0.375)	(-0.364)	(-0.259)	(-0.106)	(0.0267)	(-0.789)	(-0.668)
Big4	0.118***	0.551***	0.126***	0.582***	0.110***	0.518***	0.118***	0.555***
	(4.298)	(4.466)	(4.157)	(4.301)	(3.254)	(3.388)	(3.436)	(3.565)
Opinion	0.0378	0.168	0.0456	0.206	0.0393	0.184	0.0573	0.268
	(1.167)	(1.103)	(1.271)	(1.220)	(1.081)	(1.088)	(1.538)	(1.518)
SOE	0.0173	0.0782	0.0164	0.0758	0.0192	0.0921	0.0100	0.0478
	(1.429)	(1.366)	(1.247)	(1.208)	(1.420)	(1.412)	(0.727)	(0.716)
Pollute	0.00879	0.0378	0.0291	0.142	0.0192	0.0748	0.0222	0.0974
	(0.579)	(0.504)	(1.533)	(1.557)	(0.788)	(0.642)	(0.914)	(0.827)
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Province FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Cluster by Firm	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	11,040	11,040	9,547	9,547	8,481	8,481	8,232	8,232
R^2/Pseudo R^2	0.083	0.066	0.082	0.0657	0.079	0.064	0.077	0.0619

Table 4: Earnings Response Coefficients of Polluting and Non-Polluting Firms

This table reports the results of OLS regressions examining the effect of the introduction of the air quality monitoring system on the earnings response coefficients. Our sample contains 752 polluting firms and 1,659 non-polluting firms. The dependent variables are buy-and-hold abnormal returns where the benchmark returns are equal-weighted in Column 1, free float value-weighted in Column 2, and total market value-weighted market returns in Column 3. The coefficient on the variable UE is the earnings response coefficient for non-polluting firms before 2012, and the coefficient on the variable $UE \times AMS \times Pollute$ captures the effect of implementing new environmental standards on polluting firms' earnings response coefficient. T-statistics, shown in parentheses, are computed based on standard errors clustered by firms. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

	(1)	(2)	(3)
Dependent Variable	BHAR-EW	BHAR-FVW	BHAR-TVW
UE	0.988***	0.993***	0.992***
	(6.475)	(6.511)	(6.503)
UE × AMS × Pollute	-0.620**	-0.644**	-0.631**
	(-2.014)	(-2.093)	(-2.049)
UE × Pollute	-0.466**	-0.454**	-0.455**
	(-2.088)	(-2.037)	(-2.041)
UE × AMS	0.395*	0.397*	0.391*
	(1.868)	(1.877)	(1.850)
AMS × Pollute	-0.126***	-0.123***	-0.123***
	(-5.686)	(-5.548)	(-5.551)
Observations	9,858	9,858	9,858
R^2	0.053	0.056	0.060

Table 5: Earnings Management and Political Costs

This table reports the results of OLS regressions examining the effect of the introduction of the air quality monitoring system on the magnitude of firms' earnings management, conditional on proxies for firms' political costs. These proxies are firm size in Panel A and profit growth in Panel B. Our sample contains 759 polluting firms and 1,696 non-polluting firms, and we split the sample into two sub-samples based on the conditional variables. The first (last) two columns in Panel A are results from the sample that contains firms with above (below)-median total assets in 2011. The first (last) two columns in Panel B are results from the sample that contains firms with positive (non-positive) changes in the net profit growth rate in 2011. The dependent variable is the absolute discretionary accruals. Definitions for other variables can be found in Table 1. T-statistics (χ^2-statistics in Column 5), shown in parentheses, are computed based on standard errors clustered by firms. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

Panel A: Firm Size					
	(1)	(2)	(3)	(4)	(5)
Size Group	Large		Small		Difference
Dependent Variable	$\|DA\|$	$\|DA\|$	$\|DA\|$	$\|DA\|$	Coefficient (2) - (4)
AMS × Pollute	0.0268***	0.0261***	0.00903*	0.00889*	0.0172**
	(4.479)	(4.497)	(1.777)	(1.763)	(5.074)
Size		-0.00127		-0.00007	
		(-0.580)		(-0.0362)	
Lev		0.0902***		0.0612***	
		(7.440)		(6.573)	
ROA		0.272***		0.0513	
		(5.975)		(0.864)	
Loss		0.0176***		0.00618	
		(3.702)		(1.068)	
Indep		-0.0301		-0.0197	
		(-1.046)		(-0.680)	
Dual		0.00589		-0.00418	
		(1.068)		(-1.415)	
Board		-0.0278***		-0.0201**	
		(-2.696)		(-2.265)	
Top1		0.00549		-0.00410	
		(0.247)		(-0.252)	
Top5		0.0294		0.0218	
		(1.600)		(1.466)	
Big4		-0.0144***		-0.0193*	
		(-2.813)		(-1.904)	
Opinion		-0.0151*		-0.0163*	
		(-1.834)		(-1.854)	
SOE		-0.0144***		-0.0133***	
		(-3.283)		(-3.847)	
Pollute	-0.0210***	-0.0171***	-0.00732	-0.00693	
	(-3.840)	(-3.212)	(-1.631)	(-1.562)	
Observations	4,811	4,811	6,229	6,229	
R-squared	0.048	0.080	0.016	0.035	

Panel B: Profit Growth					
	(1)	(2)	(3)	(4)	(5)
Profit Growth Group	Large		Small		Difference
Dependent Variable	$\|DA\|$	$\|DA\|$	$\|DA\|$	$\|DA\|$	Coefficient (2) - (4)
AMS × Pollute	0.0332***	0.0319***	0.0131***	0.0127***	0.0192**
	(3.835)	(3.870)	(2.890)	(2.842)	(4.267)
Size		-0.00187		-0.00294**	
		(-0.726)		(-1.984)	
Lev		0.0596***		0.0776***	
		(3.667)		(8.669)	
ROA		0.222**		0.119**	
		(2.308)		(2.426)	
Loss		0.0239***		0.00825*	
		(2.921)		(1.814)	
Indep		-0.00938		-0.0277	
		(-0.225)		(-1.255)	
Dual		-0.000629		-0.000878	
		(-0.0966)		(-0.291)	
Board		-0.0261*		-0.0258***	
		(-1.816)		(-3.390)	
Top1		0.0638**		-0.0156	
		(2.561)		(-0.969)	
Top5		0.0126		0.0350**	
		(0.540)		(2.454)	
Big4		-0.0161		-0.0177***	
		(-1.617)		(-3.640)	
Opinion		-0.0340		-0.0121*	
		(-1.350)		(-1.904)	
SOE		-0.0119**		-0.0174***	
		(-2.163)		(-5.108)	
Pollute	-0.0188***	-0.0165**	-0.0134***	-0.0116***	
	(-2.698)	(-2.476)	(-3.107)	(-2.733)	
Observations	2,280	2,280	8,760	8,760	
R-squared	0.055	0.088	0.018	0.044	

Table 6: Earnings Management and Firms' Locations

This table reports the results of OLS regressions examining the effect of the introduction of the air quality monitoring system on the magnitude of firms' earnings management based on the firm headquarters' location. In Panel A, we split the sample into two sub-samples based on the distance from the closest monitoring station. Data on the monitoring stations' locations are collected from the Hong Kong University of Science and Technology Atmospheric & Environmental Database, which covers 1,045 stations from 2010 to 2014. The first (last) two columns are results from the sample that contains firms located within (outside) the 3km radius of a monitoring station site. In Panel B, we split the sample based on the Fan Gang Marketization Index value (Fan et al. (2011)). The first (last) two columns are results from the sample that contains firms located in the province with above (below)-median Fan Gang Marketization Index value in 2011. The dependent variable is the absolute discretionary accruals. Definitions for other variables can be found in Table 1. T-statistics (χ^2-statistics in Column 5), shown in parentheses, are computed based on standard errors clustered by firms. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

	(1)	(2)	(3)	(4)	(5)
Distance to Station Group	$<= 3km$		$> 3km$		Difference
Dependent Variable	$\|DA\|$	$\|DA\|$	$\|DA\|$	$\|DA\|$	Coefficient (2) - (4)
AMS × Pollute	0.0227***	0.0227***	0.0104*	0.00915*	0.0136*
	(3.901)	(3.992)	(1.945)	(1.724)	(3.067)
Size		-0.00358*		-0.00254	
		(-1.899)		(-1.618)	
Lev		0.0758***		0.0717***	
		(6.812)		(6.355)	
ROA		0.145**		0.130**	
		(2.434)		(2.027)	
Loss		0.0106*		0.0137**	
		(1.943)		(2.298)	
Indep		-0.00290		-0.0411	
		(-0.107)		(-1.450)	
Dual		0.000274		-0.000477	
		(0.0590)		(-0.152)	
Board		-0.0175*		-0.0315***	
		(-1.874)		(-3.255)	
Top1		-0.00421		0.000214	
		(-0.211)		(0.0112)	
Top5		0.0294*		0.0359*	
		(1.798)		(1.952)	
Big4		-0.0108*		-0.0218***	
		(-1.811)		(-3.436)	
Opinion		-0.0132		-0.0191**	
		(-1.304)		(-2.507)	
SOE		-0.0162***		-0.0150***	
		(-3.888)		(-3.866)	
Pollute	-0.0187***	-0.0160***	-0.00891*	-0.00679	
	(-3.551)	(-3.168)	(-1.860)	(-1.417)	
Observations	5,530	5,530	5,510	5,510	
R-squared	0.029	0.053	0.018	0.043	

Panel B: Marketization Index					
	(1)	(2)	(3)	(4)	(5)
Marketization Group	High		Low		Difference
Dependent Variable	$\|DA\|$	$\|DA\|$	$\|DA\|$	$\|DA\|$	Coefficient (2) - (4)
AMS × Pollute	0.0142***	0.0136***	0.0270**	0.0252**	-0.0115
	(3.364)	(3.273)	(2.547)	(2.492)	(1.127)
Size		-0.00393***		0.00144	
		(-3.058)		(0.393)	
Lev		0.0775***		0.0581***	
		(9.573)		(3.007)	
ROA		0.124***		0.211**	
		(2.628)		(2.043)	
Loss		0.0115***		0.0173*	
		(2.620)		(1.811)	
Indep		-0.0319		0.0308	
		(-1.532)		(0.622)	
Dual		-0.00138		0.00196	
		(-0.524)		(0.228)	
Board		-0.0198***		-0.0387**	
		(-2.776)		(-2.421)	
Top1		0.0232*		-0.101**	
		(1.761)		(-2.265)	
Top5		0.0154		0.0994**	
		(1.362)		(2.399)	
Big4		-0.0160***		-0.00993	
		(-3.549)		(-0.703)	
Opinion		-0.0126*		-0.0294**	
		(-1.689)		(-2.164)	
SOE		-0.0173***		-0.00800	
		(-5.546)		(-1.198)	
Pollute	-0.0131***	-0.0109***	-0.0192**	-0.0135	
	(-3.387)	(-2.869)	(-2.031)	(-1.466)	
Year FE	Yes	Yes	Yes	Yes	
Province FE	Yes	Yes	Yes	Yes	
Cluster by Firm	Yes	Yes	Yes	Yes	
Observations	8,610	8,610	2,430	2,430	
R^2	0.017	0.047	0.022	0.047	

Table 7: Earnings Management and External Factors

This table reports the results of OLS regressions examining the effect of the introduction of the air quality monitoring system on the magnitude of firms' earnings management, conditional on the level of customer concentration in Panel A, trade credit in Panel B, and industry competition in Panel C. Our sample contains 759 polluting firms and 1,696 non-polluting firms, and we split the sample into two sub-samples based on the conditional variables. The first (last) two columns in Panel A are results from the sample that contains firms with below (above)-industry-median customer concentration measured by the proportion of sales to the largest five customers in 2011. The first (last) two columns in Panel B are results from the sample that contains firms with below (above)-industry-median trade credit measured by the account payable to sales ratio in 2011. The first (last) two columns in Panel C are results from the sample that contains firms with above (below)-industry-median industry Herfindahl-Hirschman Index in 2011. The dependent variable is the absolute discretionary accruals. Definitions for other variables can be found in Table 1. T-statistics (χ^2-statistics in Column 5), shown in parentheses, are computed based on standard errors clustered by firms. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

Panel A: Customers

	(1)	(2)	(3)	(4)	(5)
Customer Concentration Group	High		Low		Difference
Dependent Variable	$\|DA\|$	$\|DA\|$	$\|DA\|$	$\|DA\|$	Coefficient (2) - (4)
AMS × Pollute	-0.00534	-0.00522	0.0370***	0.0365***	-0.0418***
	(-0.995)	(-0.998)	(5.802)	(5.855)	(26.360)
Size		-0.00488***		-0.000664	
		(-3.917)		(-0.288)	
Lev		0.0614***		0.0791***	
		(5.604)		(7.515)	
ROA		0.111		0.166***	
		(1.474)		(4.344)	
Loss		0.0147**		0.00965*	
		(2.458)		(1.917)	
Indep		-0.00600		-0.0345	
		(-0.238)		(-1.148)	
Dual		-0.000115		0.00107	
		(-0.0364)		(0.235)	
Board		-0.0142*		-0.0295***	
		(-1.799)		(-2.985)	
Top1		-0.0200		0.0196	
		(-1.318)		(0.868)	
Top5		0.0411***		0.0183	
		(2.822)		(0.932)	
Big4		-0.0135***		-0.0154**	
		(-3.006)		(-2.220)	
Opinion		-0.0230**		-0.0117	
		(-2.322)		(-1.324)	
SOE		-0.0155***		-0.0122***	
		(-4.165)		(-2.927)	
Pollute	0.00438	0.00685	-0.0347***	-0.0305***	
	(0.924)	(1.455)	(-5.811)	(-5.420)	
Year FE	Yes	Yes	Yes	Yes	
Province FE	Yes	Yes	Yes	Yes	
Cluster by Firm	Yes	Yes	Yes	Yes	
Observations	5,608	5,608	5,432	5,432	
R^2	0.016	0.042	0.036	0.060	

Panel B: Suppliers					
	(1)	(2)	(3)	(4)	(5)
Trade Credit Group	High		Low		Difference
Dependent Variable	$\|DA\|$	$\|DA\|$	$\|DA\|$	$\|DA\|$	Coefficient (2) - (4)
AMS × Pollute	-0.000502	-0.00156	0.0476***	0.0480***	-0.0495***
	(-0.129)	(-0.411)	(5.511)	(5.396)	(26.644)
Size		-0.00344***		-0.00316	
		(-3.228)		(-1.057)	
Lev		0.0623***		0.0963***	
		(6.907)		(6.229)	
ROA		0.112*		0.177***	
		(1.888)		(2.780)	
Loss		0.0145***		0.00340	
		(2.892)		(0.438)	
Indep		-0.0153		-0.00823	
		(-0.793)		(-0.186)	
Dual		0.00301		-0.00291	
		(1.192)		(-0.377)	
Board		-0.0133**		-0.0443***	
		(-2.106)		(-3.061)	
Top1		-0.00790		-0.00176	
		(-0.701)		(-0.0532)	
Top5		0.0301***		0.0440	
		(2.734)		(1.506)	
Big4		-0.0149***		-0.0139	
		(-3.733)		(-1.641)	
Opinion		-0.0133**		-0.0153	
		(-2.045)		(-1.015)	
SOE		-0.0108***		-0.0229***	
		(-3.931)		(-3.656)	
Pollute	0.00233	0.00409	-0.0436***	-0.0398***	
	(0.691)	(1.218)	(-5.151)	(-4.672)	
Year FE	Yes	Yes	Yes	Yes	
Province FE	Yes	Yes	Yes	Yes	
Cluster by Firm	Yes	Yes	Yes	Yes	
Observations	7,518	7,518	3,522	3,522	
R^2	0.018	0.043	0.033	0.062	

Panel C: Competitors					
	(1)	(2)	(3)	(4)	(5)
Industry Competition Group	High HHI		Low HHI		Difference
Dependent Variable	$\|DA\|$	$\|DA\|$	$\|DA\|$	$\|DA\|$	Coefficient (2) - (4)
AMS × Pollute	0.00320	0.00359	0.0194***	0.0185***	-0.0149
	(0.385)	(0.438)	(4.347)	(4.231)	(2.628)
Size		-0.00584***		-0.00211	
		(-2.671)		(-1.401)	
Lev		0.0658***		0.0756***	
		(4.186)		(8.518)	
ROA		0.232***		0.129***	
		(3.007)		(2.657)	
Loss		0.0156*		0.0117***	
		(1.817)		(2.611)	
Indep		-0.00128		-0.0257	
		(-0.0337)		(-1.135)	
Dual		0.00137		-0.000982	
		(0.258)		(-0.321)	
Board		-0.00291		-0.0295***	
		(-0.214)		(-3.974)	
Top1		-0.0121		0.00279	
		(-0.588)		(0.175)	
Top5		0.0571***		0.0235*	
		(2.839)		(1.667)	
Big4		-0.0254***		-0.0162***	
		(-2.993)		(-3.278)	
Opinion		0.00593		-0.0232***	
		(0.490)		(-2.995)	
SOE		-0.00243		-0.0183***	
		(-0.446)		(-5.595)	
Pollute	0.00763	0.0123	-0.0185***	-0.0157***	
	(0.992)	(1.576)	(-4.471)	(-3.960)	
Observations	1,835	1,835	9,205	9,205	
R^2	0.029	0.064	0.022	0.048	