Financial Reporting during Gloomy Days: Air Pollution and Real Earnings Management

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Abstract

We investigate whether long-term exposure to polluted air affects a firm's real earnings management (REM). Using a sample of U.S. listed firms and *Visibility*, a novel measure of air pollution, we find that firms whose managers and employees are exposed to polluted air are more likely to engage in short-term-oriented REM. However, these firms do not show significant differences in accrual-based earnings management (AEM). A one standard deviation decrease in *Visibility* is associated with a 24.3 percent increase in REM. Interestingly, this effect is disproportionately associated with the overproduction of inventory and cuts in discretionary expenses, rather than in the manipulation of sales prices or credit terms. The impact of polluted air on REM is more pronounced in firms with high analyst pressure, no credit rating, low institutional ownership, or poor corporate governance. The results suggest the existence of earnings-target-oriented managerial myopia among firms exposed to polluted air. Cognitive biases among managers and reduced employee productivity, both induced by air pollution, are potential channels through which polluted air triggers firms' myopic earnings management behaviors.

Keywords: polluted air; earnings management; managerial myopia; environmental externality

JEL codes: G3, M14, M41, Q56

1. Introduction

Managerial myopia, which refers to the inclination of managers to prioritize short-term objectives over long-term value-adding projects, is a widely recognized as well as extensively researched phenomenon in the business world (e.g. Graham et al., 2005; He and Tian, 2016). At the intersection of managerial myopia and earnings management, real earnings management (REM) has become an important issue attracting the attention of academia. REM allows managers to meet near-term earnings benchmarks by manipulating firms' real operating, investing, and financing activities, which can dampen firms' ability to generate cash flows in future periods. Although costly, managers prefer REM to AEM (e.g., Graham et al., 2005) because REM is less likely to be detected (Cohen et al., 2008; Cohen and Zarowin, 2010; Zang, 2012) and can be implemented continuously throughout the year (Roychowdhury, 2006).

In this paper, we focus on polluted air as a determinant of REM. Managers and employees exposed to polluted air may experience myopia due to changes in their neuro-cognitive functioning processes (Tzivian et al., 2015), heightened levels of aggressiveness (Berman et al., 2019; Bondy et al., 2020; Burkhardt et al., 2019; Lu et al., 2018), and hormonal changes that alter inter-temporal decision-making, leading them to focus on the present (Cho et al., 2022; Li et al., 2017; Riis-Vestergaard et al., 2018).[1] As a result, managers of the affected firms are more likely to engage in earnings management to maximize short-term financial performance. Furthermore, prolonged exposure to polluted air can decrease managers' and employees' productivity (Chang et al., 2016, 2019; Lichter et al., 2017). To compensate for the lower-than-expected financial performance resulting from this

[1] Literature documents that polluted air negatively affects people's cognitive processes (e.g. Lercher et al., 1995). It also impacts decision-making processes, such as investment decisions by investors (Shafi and Mohammadi, 2020), decisions made by U.S. immigration judges (Heyes and Saberian, 2019), decisions to purchase automobiles (Busse et al., 2015), and investor behavior in both the primary market (Sun et al., 2023) and the secondary market (Saunders, 1993).

productivity decrease, managers may be motivated to conduct earnings management.

However, prior studies on the effect of environmental conditions on earnings management mainly focus on AEM and have not addressed how these conditions affect a firm's use of both AEM and REM. In this study, we investigate earnings-target-oriented managerial myopia as discussed by Graham et al. (2005), and focus on the myopic manipulation of operating and investing activities in particular. We examine the influence of long-term exposure to air pollution on REM in addition to its influence on AEM.

Examining the relation between air pollution and REM is important for several reasons. First, although prior literature on earnings management has broadened its scope to reporting the impact of air pollution on AEM (Cho et al., 2022), it has not investigated this topic in relation to REM, a prevalent earnings management practice despite its costly impact on a firm’s long-term viability (Graham et al., 2005; Irani and Oesch, 2016). Therefore, it is worth examining whether managers increase or decrease REM and substitute it for AEM in response to air pollution. Second, unlike AEM, REM is affected by the activities and decisions of not only the CEO but also other employees including key subordinate managers.[2] Because a firm’s CEO and employees are all plausibly influenced by the surrounding air quality, the effect of polluted air could be more pronounced on REM than on AEM. Finally, REM is implemented continuously throughout the year, and air pollution also affects managers’ and employees’ cognitive functioning and productivity continuously. Therefore, we can investigate the cumulative impact of polluted air on a firm’s strategic reporting behaviors by focusing on REM as well as on AEM.

We measure the air pollution using the visibility indices from the National Oceanic and

[2] Compared to their control over AEM, key subordinate executives have more direct control over real activities such as research and development (R&D) expenditures, production volumes, and sales decisions according to Cheng et al., (2016), who document that key subordinate executives play a crucial role in REM. They stress the importance of examining the characteristics of other stakeholders beyond the CEO when discussing REM.

Atmospheric Administration (NOAA). Particulate matter pollution is a major cause of reduced visibility in the United States (US-EPA, 2023). We use visibility, defined as the visual range in miles, as a proxy for air pollution not only because it is strongly associated with the level of air pollution and affects people's cognitive functioning (Gath-Morad et al., 2021) but also because changes in visibility are plausibly exogenous and orthogonal to the attributes of REM (Shafi and Mohammadi, 2020), yielding an advantageous identification strategy. In the robustness checks section, we find similar results using direct measures of air pollution; specifically, the population-weighted annual mean of particulate matter 2.5 (PM 2.5).[3]

We collect firm characteristics of 2,220 firms across the United States from Compustat and combine them with the weather data reported by the nearest weather station to each firm during the fiscal year. Our final sample consists of 11,590 firm-year observations for the period 2003-2017.

We investigate the relation between REM and visibility and find that firms exposed to polluted air for a relatively long period (an entire year prior to the firm's fiscal year-end) are more likely to engage in REM. Interestingly, polluted air does not affect firms' AEM. We conjecture that managers in strong legal regime countries such as the U.S. conduct earnings management in response to the polluted air mainly using REM because AEM is more easily detected and severely punished under strong legal institutions (Francis et al., 2016). As for individual REM measures, we further find that firms increase earnings using overproduction and discretionary expense cuts but not through excessive sales price discounts or lenient credit terms. Manipulating sales prices or credit terms can be easily detected by a firm's auditor, and managers usually do not have good justifications. In contrast, overproduction or deferment of research and development (R&D) investment is more difficult to detect, and managers can justify these actions more easily because production volume and

[3] The data is collected within CBSAs (Core-Based Statistical Areas), which comprise two distinct types: Metropolitan Statistical Areas (MSAs) and Micropolitan Statistical Areas (µSAs). PM 2.5 is computed with the weight of populations of the cities located in each MSA or µSA and then averaged across days in a given year.

R&D investment are influenced not only by managerial opportunism but also by market demand and competitions. In cross-sectional analyses, we also find that the REM-increasing effect of air pollution is exacerbated (mitigated) by external monitoring by analysts (credit rating agencies or institutional investors) and is mitigated by good corporate governance and that this effect is more pronounced in knowledge-intensive than in labor-intensive industries.

This paper contributes to the literature in several ways. First, this is the first study to investigate the effect of air pollution on REM. While many prior studies examine the effect of air quality on people's physical and psychological states (Pope, 2000; Power et al., 2015), labor supply (Hanna and Oliva, 2015), productivity (Chang et al., 2016, 2019; Lichter et al., 2017), and analyst forecast optimism (Dong et al., 2021), studies on the relation between air quality and financial reporting properties are relatively scant. Using a sample of Chinese firms, Cho et al. (2022) document that managers exposed to polluted air are more likely to engage in earnings management because they become more unethical due to the psychological bias caused by air pollution. However, their study focuses on AEM and remains silent about REM. The inferences derived from the effect of air pollution on AEM may or may not be extended to the effect of air pollution on REM because AEM and REM can be complementary or substitutive depending on their relative costs (Zang, 2012) and the country-level legal regime (Choi et al., 2018). Using a sample of U.S. firms, we find that air pollution increases REM but does not affect AEM, which contradicts the findings of Cho et al. (2022). We attribute this divergence to the differences in the legal and institutional environments between the U.S. and China. Because managers substitute REM for AEM when the relative cost of AEM (REM) is high (low), they resort more to REM in a developed country such as the U.S. but depend more on AEM in a developing country such as China where the relative costs of AEM vs. REM are opposite. Our paper is also different from Cho et al. (2022) in that we adopt a more refined measure of air pollution using visibility, which is an indirect measure of air pollution but less vulnerable to data manipulation concerns that are associated with direct air pollution measures. We also investigate the moderating effects of internal governance and external monitoring and find that the pressure from analysts and poor corporate governance exacerbate managers' opportunistic REM activities in response to air pollution, which is not examined in Cho et al. (2022). Because the extent of opportunistic financial reporting is very sensitive to the degree of internal and external monitoring or pressure, this test helps enhance our understanding of the interactive roles between these moderating factors and air pollution.

Second, this paper expands the scope of the literature on the determinants of REM. Thus far, research on this topic has suggested various determinants such as capital market pressure (Haga et al., 2018a), external governance (Chi et al., 2011; Roychowdhury, 2006; Choi et al., 2018), internal corporate governance (Cheng et al., 2016), the stringency of accounting standards (Cohen et al., 2008; Ho et al., 2015), and analyst coverage (He and Tian, 2013). We introduce air pollution as a new determinant of REM. While air pollution is not a new research topic, its relation to REM is novel. With environment-related topics making headlines in the financial press, it is timely and relevant to investigate the impact of air pollution on REM.

Third, this paper introduces visibility as a new measure of air pollution. Lu (2020) argues that both actual and perceived air quality matter to individuals' psychological, economic, and social outcomes and welfare. The majority of prior literature uses AQI or PM to proxy for pollution and poor air quality. However, these metrics may be vulnerable to data manipulation issues, leading to inaccurate assessments of actual air pollution levels (Zou, 2021). By using visibility as a more accurate proxy for the level of actual air pollution, our study is free from this data manipulation issue. In the robustness checks section, we also use PM 2.5 and the explained portion of visibility by PM 2.5 to measure air pollution and find consistent results.

Our study has an important policy implication. Accounting regulators have striven to increase the quality of financial reporting using various accounting standards and rules. However, for firms located in severely polluted areas, regulators' efforts can be thwarted in deterring firms from engaging in earnings management. Our finding suggests that by working with environmental regulators to improve air quality, accounting regulators can more efficiently achieve their goal of increasing reporting quality.

The remainder of the paper is organized as follows. Section 2 provides a summary of prior literature based on which we develop our hypotheses. Section 3 describes the sample, data, and variable measurements. Section 4 introduces our empirical specification and reports the results of the main analyses. Section 5 presents the results of cross-sectional tests. Section 6 discusses the results of robustness checks. Finally, section 7 concludes.

2. Related Literature and Hypothesis Development

2.1. Earnings Management

Earnings management is a purposeful intervention in the financial reporting process by management to mislead stakeholders about the true performance of the firm or to alter contractual outcomes that depend on financial reports (Healy and Wahlen, 1999). Manipulating accruals and real activities are two means to manage earnings (Dechow et al., 2010; Dechow and Skinner, 2000; Fields et al., 2001; Healy and Wahlen, 1999; Schipper, 1989). Examples of accrual-based earnings management (AEM) include under-provisioning for bad debt expenses and delaying asset write-offs (Roychowdhury, 2006). Besides AEM, managers also have incentives to manipulate real activities to meet certain earnings targets. Real earnings management (REM) is defined as managerial actions that deviate from normal business practices to meet certain earnings thresholds, such as cutting R&D expenditures, reducing capital investments, boosting production and sales, and disposing of long-term assets (Roychowdhury, 2006).

The determinants of earnings management behaviors have been widely explored in the prior literature and can be divided into two categories – economic incentives and psychological factors. Economic incentives include smoothing earnings streams, boosting stock prices (Graham et al., 2005), and increasing the CEO's compensation tied to the stock price (Bergstresser and Philippon, 2006), among others. Degeorge et al. (1999) and Burgstahler and Dichev (1997) provide evidence of firms managing earnings to avoid losses or earnings decreases. These studies posit that firms' executives, acting in self-interest and, at times, for stakeholders, manage earnings to sustain recent performance and meet analyst expectations. Another strand of literature posits that the personal and psychological traits of firm managers may also affect a firm's earnings management activities. Bamber et al. (2010) observe from manager-specific fixed effects that there exist systematic, lasting differences in managers' unique disclosure styles, which are associated with a manager's background. Schrand and Zechman (2012) report that overconfident executives are more likely to exhibit an optimistic bias and are more likely to make intentional misstatements. Ham et al. (2017) find that CFO narcissism is associated with more earnings management, less timely loss recognition, weaker internal control quality, and a higher probability of restatements. Davidson et al. (2015) find that CEOs and CFOs with a record of legal infractions are more likely to perpetrate fraud. These studies all allude to the association between the individual characteristics of a firm's financial executives and the firm's earnings management practice in general.

2.2. Real Earnings Management

Prior literature has identified various determinants of REM. They include capital market pressure (Haga et al., 2018a; Li and Xia, 2021), labor union pressure (Chang et al., 2022), CEO social capital (Griffin et al., 2021), geographic dispersion (Shi et al., 2015), internal corporate governance (Cheng et al., 2016), and external corporate governance (Bushee, 1998). Existing studies suggest that a reasonable amount of corporate governance could constrain REM.[4]

Good corporate governance mitigates managers' opportunistic earnings management in general. However, excessive governance can pressure decision-makers and thus result in unintended REM (Chan et al., 2015). For instance, tougher board monitoring (Ge and Kim, 2014), stringent financial reporting standards (Cohen et al., 2008; Ho et al., 2015), the adoption of IFRS-convergent accounting standards (Ho et al., 2015), higher auditor quality and industry expertise (Chi et al., 2011; Cohen and Zarowin, 2010; Roychowdhury, 2006), and larger analyst coverage (Irani and Oesch, 2016) may all induce firms to engage in REM substituting for AEM. This is because AEM is more detectable under such a stringent governance system.

In addition to these factors, environmental elements can serve to potentially induce firm management to engage in earnings management. For example, using international data, Ding et al. (2021) find that climate risk can damage corporate assets and decrease business productivity, motivating managers to conduct both AEM and REM.

2.3. Consequences of Air Pollution

There exists decades-old literature on the impact of environmental conditions on mood and decision-making (see Cunningham (1979) and Schwarz and Clore (1983) for details). In finance, researchers have extended this research stream to investigating the effect of weather on stock market prices and trading behavior (Goetzmann et al., 2015; Hirshleifer and Shumway, 2003; Kamstra et al., 2003; Saunders, 1993), bidding decisions in the primary market (Sun et al., 2023), crowdfunding and investment decisions (Shafi and Mohammadi, 2020), institutional investor responses (Jiang et al., 2021), and analyst forecast properties in general (DeHaan et al., 2017) and in relation to company

[4] Cheng et al. (2016) show that subordinate executives, independent boards, and boards of directors all play a role in constraining a firm's REM.

visits in particular (Dong et al., 2021).

Visibility, defined as the visual range in miles, is a proxy for the level of air pollution. Prior research has documented that reduced visibility is largely attributed to light-scattering pollutants such as sulfate and nitrate compounds. Diederen et al. (1985) study the ambient air quality monitored in the Netherlands during 1979-1981. They find that the total light extinction is predominantly due to light scattering by fine particles, with the remainder caused by light scattering by gases and light absorption by gases and particles.[5] Thach et al. (2010) assess the short-term effects of daily visibility loss on mortality and find that visibility provides a useful proxy for the environmental health risks from ambient air pollutants.[6] In summary, visibility can serve as a proxy for air pollutant density or pollution levels.

Early studies on the consequences of air pollution mainly focus on how pollution affects people's physical and psychological states. In terms of physical outcomes, Pope (2000) finds that air pollution induces cardiopulmonary disease, increases respiratory problems, decreases lung function, and impacts other physiological changes. Beatty and Shimshack (2014) report that marginal increases in air pollutants are associated with increases in children's contemporaneous respiratory treatments. In terms of psychological consequences, Power et al. (2015) document that exposure to fine particulate matter (PM 2.5) is associated with anxiety, with more recent exposures potentially more relevant than more distant exposures. Lercher et al. (1995) reveal that fatigue, exhaustion, low mood, nervousness, eye irritation, and stomachaches are significantly associated with air quality. Lim et al. (2012) suggest that increases in PM 10, NO_2, and O_3 may increase symptoms of depression among the elderly.

[5] The relative influence of the mass concentration of fine aerosol particles on visibility is a factor more pronounced than the influence of relative humidity. In addition, White and Roberts (1977) propose that the estimated contribution of large stationary sources of sulfur dioxide to the reduction of visibility is comparable with that of an automobile because of the high scattering efficiency of sulfates.

[6] Specifically, Thach et al. (2010) propose that visibility provides a valid approach for the assessment of 1) the public health impacts of air pollution and 2) the benefits of air quality improvement measures in developing countries where pollutant monitoring data are scarce.

Recent literature has focused on assessing the impact of air pollution on behavioral aspects such as worker productivity. He et al. (2019) examine day-to-day fluctuations in worker-level output at two manufacturing sites in China and find that a substantial +10 μg/m^3 PM 2.5 variation sustained over 25 days reduces daily output by one percent. Lichter et al. (2017) find statistically significant negative effects of air pollution on soccer players' productivity, measured by the total number of passes per match. Chang et al. (2019) focus on two call centers in China and find that higher levels of air pollution decrease worker productivity by reducing the number of calls that workers complete each day. Lavy et al. (2015) report a robust negative relation between pollution exposure and standardized test scores among Israeli high school students on high-stakes tests for the period 2000-2002. Consistent with the results above, Hanna and Oliva (2015) exploit an exogenous variation in pollution due to the closure of a large refinery in Mexico City and find that the closure resulted in less pollution and an increase in work hours per week. Additionally, the literature indicates a positive association between air pollution and unethical behaviors or crimes. For example, Berman et al. (2019) find that changes in ambient air pollution are associated with a greater risk of violent behavior, regardless of community type. Using a nine-year panel of 9,360 U.S. cities, Lu et al. (2018) show that air pollution predicts six major categories of crimes, which is mediated by anxiety. Using daily administrative data of London for the period 2004-2005, Bondy et al. (2020) find that air pollution has a positive and statistically significant impact on overall crime and several major crime categories.

2.4. Hypothesis Development

Recent literature provides multiple suggestions on how air pollution may cause myopia and inefficient decision-making. First, air pollution impedes cognitive functioning (Tzivian et al., 2015; Zhang et al., 2018). Zhang et al. (2018) find that long-term exposure to polluted air impedes cognitive performance on verbal and math tests. Tzivian et al. (2015) show that poor air quality negatively impacts an individual's neuro-cognitive functioning. Long-term exposure to polluted air may gradually reduce and deplete one's coping capacity. This can push an individual toward his or her limits, which is often characterized by heightened levels of anxiety and tension (Vert et al., 2017).

Polluted air also affects an individual's discounting process between the present and the future. Studies document that air pollution may lead to hormonal changes that alter inter-temporal decision-making and induce individuals to focus on the present (Cho et al., 2022; Li et al., 2017; Riis-Vestergaard et al., 2018). The decision to manipulate earnings involves a trade-off between the benefits and the costs of earnings manipulation (Armstrong et al., 2013). While the benefits are often imminent, the costs (e.g., possible restatements, enforcement actions, litigations, and dismissals) may be incurred in the distant future (Karpoff et al., 2008). Haga et al. (2018b) and Kim et al. (2017) both find that present-focused people are more likely to engage in earnings management. Specifically, Haga et al. (2018b) argue that discount rates are positively associated with income-increasing earnings management. Kim et al. (2017) find that AEM and REM are less prevalent where languages do not require speakers to grammatically mark future events, indicating that earnings management is a shortsighted type of decision-making.

Second, managers engage in earnings management because of the decreased productivity of themselves and their subordinates caused by the exposure to air pollution. Polluted air has been shown to negatively affect productivity among workers (Neidell, 2017; Chang et al., 2016, 2019), professional soccer players (Lichter et al., 2017), equity analysts (Li et al., 2020), and patent inventors (Luo et al., 2022). To make up for the lower financial performance caused by decreased productivity, managers are motivated to engage in earnings management.

We note that out of these two channels through which air pollution affects earnings management, i.e., managers' focus on short-term performance and employees' productivity decrease, the former is relatively more important than the latter in our empirical setting. This is because we measure air pollution based on the firms' headquarter locations without considering their production facilities located elsewhere (see Footnote 7). Air pollution reduces both managers' and other employees' productivity. However, our air pollution measure does not reflect employees' air pollution-induced productivity decrease in the production facilities that are located in different regions from the headquarters. As a result, the effect of our air pollution measure (*Visibility*) on firms' real earnings management is explained by the following channels: 1) the myopic behavior of managers focusing on short-term performance that is caused by air pollution-induced managerial cognitive bias; 2) the air pollution-induced productivity decrease of managers (and other employees working at the production facilities located in the same regions as headquarters), but *not* other employees working at the production facilities located in different regions from headquarters.

Given that managers are exposed to polluted air throughout the entire fiscal year, not just at the year-end, REM is a more appropriate choice of earnings management than AEM. Furthermore, compared to AEM, REM is arguably a better proxy for myopia (García Osma et al., 2022; Roychowdhury, 2006) because REM dampens firms' long-term viability to a greater extent than AEM. In this regard, we hypothesize that polluted air induces managers both to conduct earnings management and to choose REM over AEM. We state our main hypothesis as follows in alternative form:

H1: *Managers of firms located in areas with air pollution are more likely to engage in REM, ceteris paribus.*

Using a sample of Chinese firms, Cho et al. (2022) document that managers exposed to a higher level of air pollution conduct more AEM. However, it remains uncertain whether this finding can be applied to our research context, which focuses on U.S. firms. Recent studies find that managers prefer REM to AEM in general (Graham et al., 2005) and that they have incentives to substitute REM for

AEM under stricter financial reporting standards (Cohen et al., 2008; Ho et al.,2015), increased analyst coverage (Irani and Oesch, 2016), greater auditor industry expertise (Chi et al., 2011), more stringent corporate governance (Chan et al., 2015), and other sources of external pressure. Francis et al. (2016) also report that REM substitutes for AEM in countries with robust legal environments such as the U.S. Thus, exposed to air pollution, managers in developing countries such as China may choose AEM as their main earnings manipulation method, while those in developed countries such as the U.S. may choose REM. In this case, unlike REM, we may not find a significant relation between air pollution and AEM for U.S. firms. Alternatively, managers in U.S. firms might use both AEM and REM in response to their exposure to polluted air but tend to rely more on REM than on AEM. Based on this discussion, we state our supplementary hypothesis on the relation between air pollution and AEM as follows in alternative form:

H2: *Managers of firms located in areas with air pollution are more likely to engage in AEM, ceteris paribus*.

3. Sample, Empirical Measures, and Summary Statistics

3.1. Sample and Data

We start with 52,593 firm-year observations from Compustat and I/B/E/S for the period 2003-2017. For each firm-year observation, we obtain the latitude and longitude coordinates of the firm's headquarter from Google Maps based on zip codes.[7] Next, for each firm, we match it with its closest weather station to obtain its surrounding weather conditions, as recorded by NOAA[8] over the one

[7] Unlike AEM, measuring *Visibility* based on a firm's headquarter location may create measurement error problems when examining the effect of polluted air on REM because various REM activities may be conducted at both a firm's headquarter and production facilities in different locations. These measurement errors, however, will produce a "conservative bias" against finding our main results because the reported inferences would be stronger if we measured *Visibility* as the employee-weighted average visibility across a firm's headquarter and production facilities.
[8] Data from NOAA for the U.S. is available for free, the use of which is unrestricted for research, education, and other

year before its fiscal year-end date[9], yielding a sample of 48,332 firm-year-station observations. Then, we aggregate the weather-related indicators for each firm-year by taking the mean, maximum, or minimum of the weather statistics as appropriate. Ultimately, we obtain 47,662 firm-year observations with complete information on air quality.[10] We remove 5,156 firm-years in financial industry (SIC 6000-6999) and 2,138 firm-years in utilities industry (SIC 4900-4999) from our sample, resulting in 40,368 firm-year observations, because the firms in these regulated industries can be subject to different accounting requirements for accruals. We drop 188 duplicate firm-year observations and retain only the observations with no missing values for any major variable included in the main analysis. Our final sample comprises 11,590 observations at the firm-year level, consisting of 2,220 unique firms for the period 2003-2017. Please refer to Table 1 for the detailed sample selection procedure.

Table 1 About Here.

3.2. Measures of Accrual-based Earnings Management (AEM)

Our proxy for accrual-based earnings management consists of two measures: *AEM (performance adjusted)* and *AEM (modified Jones).* These measures represent discretionary accruals based on Kothari et al. (2005) and the modified Jones model proposed by Dechow et al. (1995), respectively. Specifically, for *AEM (performance adjusted),* we calculate discretionary accruals as the difference between a firm's actual accruals and the normal level of accruals estimated using the performance-adjusted modified Jones model within each industry-year, where industries are defined using the two-digit standard industry classification (SIC) codes. In line with Cho et al. (2022), we also present

non-commercial activities. Details can be found on the website below:
https://www.ncei.noaa.gov/pub/data/noaa/isd-lite/.

[9] Fiscal year and fiscal month information is available for all 52,593 firm-year observations, and we assume that each firm's fiscal year end date is the last day of its fiscal year.

[10] Among the 48,332 firm-year observations, 670 observations, for which a firm is matched to multiple stations with equal distance, are dropped from our final sample.

results using discretionary accruals calculated by the modified Jones model (*AEM (modified Jones)*) and their rankings as alternative measures in our primary tests. For more detailed explanations of each measure, please refer to Appendix C.

3.3. Measures of Real Earnings Management (REM)

We derive our aggregate measure of real earnings management (*REM*) following prior studies (e.g. Cohen and Zarowin, 2010; Roychowdhury, 2006). The aggregate measure can be decomposed into three individual metrics: abnormal levels of cash flows from operations (REM_{CFO}), discretionary production costs (REM_{PROD}), and discretionary expenses (REM_{DISX}), with each measure proxying for a specific type of real activity manipulation behavior. For more detailed explanations of each measure, please refer to Appendix C.

3.4. Air Pollution Measures

Research in psychology suggests that weather factors, including rainfall, wind, temperature, air pressure, and humidity all affect people's emotional states (DeHaan et al., 2017). To create a plausible measure of polluted air, we focus on visibility (*Visibility*) obtained from NOAA for two reasons. First, environmental factors, such as pollutant and non-pollutant particles, can significantly reduce visibility. Optically, this is due to the substantial presence of these particles in the atmosphere that absorb and scatter light (Tan, 2008). Thach et al. (2010) document that visibility provides a useful proxy for the assessment of environmental health risks from ambient air pollutants. Second, Lu (2020) emphasizes that it is important to distinguish between the effects of the actual and perceived air pollution levels when considering the impacts of unpleasant air quality on psychological, social, and environmental outcomes. Prior literature mostly uses measures for actual pollution levels such as AQI or PM, which we also test in the robustness checks section, but this may potentially lead to data manipulation issues. For example, Zou (2021) finds that intermittent monitoring of environmental standards may induce strategic changes in polluting activities. Governments sometimes coordinate carbon emission reduction to meet environmental standards, which can lead to inaccurate data measures for actual levels of air pollution but has not been shown to exert any influence on the level of air pollution that people can feel.[11] Therefore, this paper uses *Visibility* to more accurately measure the level of air pollution that people can feel and examines how it affects a firm's earnings management activities.

However, given that various types of weather indicators are highly correlated (e.g., rainy days are more likely to be cloudy), the effect of visibility on our outcomes of interest may capture the impact of other omitted weather measures on earnings management behaviors. Therefore, in one of our robustness checks, in addition to *Visibility*, we include a number of weather measures as controls and find consistent results with our baseline findings for each included weather-related indicator.[12] The results suggest that the effect of *Visibility* on *REM* is mainly driven by light-scattering pollutants, rather than by the included weather measures such as the occurrences of rain or snow. Additionally, using the population-weighted annual mean of PM 2.5 leads to similar results.

Hourly air quality data is obtained from the NOAA ISD-Lite data set. NOAA provides a global surface summary of daily weather produced by the National Climatic Data Center (NCDC) headquartered in Asheville, North Carolina.[13] We link each firm to its closest available NOAA weather station.

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[11] For example, governments can encourage firms in high pollution areas to temporarily cut toxic gas emissions to meet target levels during an inspection visit by a domestic or international environmental regulatory body. However, the average air pollution throughout the year will not be reduced if firms emit more toxic gases after the inspection. Therefore, the monitored level of annual PM 2.5 would be lower than the actual level. Another problem with using actual air pollution measures is that the data are available at the city level, which is not gauged by the closest station to a firm's location, but rather, a weighted average of the PM 2.5 level of several locations within the city. As such, for a firm located at the outskirt of a city that is far away from the air-pollution-generating facilities in the city, the PM 2.5 measure would provide an overestimate for the pollution this firm is exposed to.

[12] The weather variables we include in the robustness checks are mean temperature, mean dew point, mean sea-level pressure, mean wind speed, maximum wind gust, maximum sustained wind speed, mean precipitation including rain or melted snow, minimum temperature, maximum temperature, fog occurrence, rain or drizzle occurrence, thunder occurrence, snow depth, snow occurrence, hail occurrence, and tornado occurrence. Details can be found in Section 6.

[13] The input data used for building these daily weather summaries are derived from the Integrated Surface Data (ISD), which includes global data obtained from the USAF Climatology Center located in the Federal Climate Complex with NCDC.

Based on the zip codes for each station and firm headquarters, we determine their coordinates and the distance between the two. Distances are calculated using the software, ArcGIS. The data for air quality are available for the period 2003-2017.[14]

We measure air quality for each firm within a 12-month timeframe leading up to the conclusion of their fiscal year. This approach allows us to draw meaningful comparisons between the impact of air pollution on AEM and REM, considering that REM is implemented throughout the year. It is worth noting that in our primary analysis, we use the fiscal year-end date as the reference point. However, for robustness, we also conduct alternative tests using the actual period end date, often referred to as "apdedate" in the Compustat code, as the reference point. The results obtained from these alternative tests are consistent with our primary findings (for detailed results, please refer to the Online Appendix). Moreover, it is important to note that managers tend to have stronger incentives to manipulate earnings specifically at the fiscal year-end. According to Das et al. (2009) and Dhaliwal et al. (2004), firms focus on specific line items in the income statement to manage fourth-quarter earnings to meet or beat annual earnings targets. In addition, a survey by Graham et al. (2022) documents that "sometimes companies engage in end-of-quarter practices such as delaying valuable projects to hit market expected earnings". In the Online Appendix, we alternatively focus on the last quarter's earnings management and explore its association with polluted air.[15] We calculate the mean, maximum, or minimum air quality and weather measures over the measurement window for each firm. The choice between mean, maximum, or minimum values depends on the specific measure we focus on.[16]

[14] For the specific sources of NOAA air quality data used in this paper, refer to ftp://ftp.ncdc.noaa.gov/pub/data/gsod.

[15] Since firms often conduct AEM in the last months after fiscal year-end and conduct REM for the entire fiscal year, in the Online Appendix, we conduct both three-month after fiscal year-end and one-year (and three-month) before actual year end date analyses for AEM and REM.

[16] We take the means of the daily mean temperature, mean dew point, mean sea-level pressure, mean visibility, mean wind speed, precipitation, snow depth, fog occurrence, rain occurrence, snow occurrence, hail occurrence, thunder occurrence, and tornado occurrence over a one-year measurement window; for maximum sustained wind speed, maximum wind gust, and maximum temperature, we take the maximum of these indicators over a one-year measurement window; and finally, for minimum temperature, we take the minimum value over a one-year measurement window.

In the robustness checks section, we also use the annualized level of PM 2.5 to proxy for air pollution. Our raw data are publicly available from the United States Environmental Protection Agency.[17] We adopt the population-weighted annual mean of PM 2.5 at the city level as our measure of air pollution. This variable is calculated for cities with adequate monitoring data records from 2000 to 2021. Data from exceptional events are included.

3.5. Descriptive Statistics

Table 2 presents the descriptive statistics for the firm characteristics of 11,590 firm-years in our sample. The mean values of *AEM (performance-adjusted)* and *AEM (modified Jones)* are -0.017 and -0.014, respectively, suggesting a slightly downward accrual manipulation in our sample. The mean and median values of *REM* are -0.070 and -0.052, respectively, indicating an overall downward direction of real earnings management. To eliminate the possibility that extreme values of *AEM* and *REM* contaminate our estimates, we use both the levels and the ranks of *AEM* and *REM* as our main outcomes of interest. Other firm characteristics are self-explanatory.

Table 2 About Here.

Table 3 Panel A provides the summary statistics of air quality and weather measures in our sample. The average temperature, dew point, and sea-level pressure of all station years that are matched to at least one firm in our sample are 57.49 Fahrenheit, 44.68 Fahrenheit, and 1016.47 mb, respectively. The mean *Visibility* of all station-years is 9.13 miles, and the mean wind speed is 6.15 knots. The maximum daily wind gust and the maximum sustained wind speed are 45.91 knots and 31.52 knots, respectively. In our sample, the total daily precipitation of all station years is 4.27 inches on average, and the average daily snow depth is 0.12 inch. The maximum and minimum daily temperatures are 97.40 Fahrenheit and 9.52 Fahrenheit, respectively. The incidence of fog, rain, snow, and thunder are on average 10.7

[17] The official website for the United States Environmental Protection Agency (USEPA) is: https://www.epa.gov/.

percent, 31.2 percent, 7.1 percent, and 8.1 percent, respectively. The incidences of hail and tornadoes are very rare in our sample. We also report similar statistics on firm-year level in Panel B, which are used for economic significance estimations for our main findings.

Table 3 About Here.

4. Empirical Analyses and Results

4.1. Univariate Test

Table 4 compares the extent of AEM and REM and other firm characteristics between the high and low air pollution subsamples and reports the differences using *t*-values. We divide the total sample based on the median value of *Visibility* in its annual firm-year distribution.

On average, firms in the high air pollution subsample are more likely to undertake both AEM and REM than those in the low air pollution subsample. In terms of specific REM behaviors, firms in the high air pollution subsample are more likely to overproduce, manipulate sales price/credit terms, and cut discretionary expenses.

In terms of firm characteristics, the average firm size (*Size*) of 6.85 million dollars in the high air pollution subsample is smaller than that of 6.93 million dollars in the low air pollution subsample. The propensity to report loss (*Loss*) or to belong to a litigious industry (*Litigious*) and annual stock return (*RET*) are also lower in the high air pollution subsample. In contrast, the values of book-to-market ratio (*BM*), return on assets (*ROA*), leverage (*Leverage*), firm age (*Firm Age*), propensity to be audited by a Big N auditor (*Big N*), institutional ownership (*INST%*), the propensity to have a credit rating (*Credit Rating*), and net operating assets (*NOA*) for firms in the high air pollution subsample are all higher than those in the low pollution subsample. This indicates that the former is different along a number of dimensions from the latter. This difference also warrants us to include these variables as controls in the main specification. A table that displays the correlations across firm-level characteristics can be seen in Appendix D.

Table 4 About Here.

4.2. Multivariate Regressions

To examine the effect of polluted air on a firm's earnings management behaviors, we use the following OLS regression equation as our main specification:

$$Y_{i,t} = \beta_1 Visibility_{i,t} + \boldsymbol{X}_{i,t}\gamma + \delta_j + \sigma_t + \epsilon_{i,t}, \quad (1)$$

where $Y_{i,t}$ denotes one of the earnings management measures (AEM or REM) for firm i in year t, and $Visibility_{i,t}$ is the visibility firm i is exposed to for one year prior to the end of its fiscal year t. We report the alternative three-month time window after each firm's fiscal year-end, and the one-year (and three-month) time window prior to the actual period end date in the Online Appendix. $X_{i,t}$ represents control variables including yearly mean of fog occurrences (*Fog*)[18], firm size (*Size*), book-to-market ratio (*BM*), return on assets (*ROA*), leverage (*Leverage*), firm age (*Firm Age*), an indicator for Big N auditor (*Big N*), auditor tenure (*Auditor Tenure*), loss dummy (*Loss*), annual sales growth (*Sales Growth*), litigious industry dummy (*Litigious*), institutional ownership (*INST%*), annual stock return (*RET*), standard deviation of sales for the past three years (*StdSales*), net operating assets (*NOA*) (when the dependent variable is *AEM*), and the Herfindahl–Hirschman Index per industry-year (*HHI*) (when the dependent variable is *REM*). We also include *REM* (*AEM*) on the right-hand side when the dependent variable is *AEM* (*REM*) to account for the complementary or substitutive relation between AEM and REM. Industry fixed effects (δ_j) and year fixed effects (σ_t) are controlled in all specifications. Standard errors are clustered by industry and by year in our baseline specifications.

[18] Visibility is significantly affected by fog but fog is not a pollutant particle. Therefore, the portion of low visibility caused by fog is not expected to affect managers' cognitive functioning or productivity. To estimate the effect of air pollution-driven visibility on REM that is orthogonal to fog, we control yearly mean of fog occurrences (*Fog*) in our main regression model.

Table 5 presents the impact of polluted air on AEM and REM by regressing Eq. (1) for the level and the ranking of AEM/REM. Column 1 shows that *Visibility* has no significant relation with AEM estimated by the performance-adjusted modified Jones model, which is consistent with our prediction that managers prefer REM to AEM in countries with strong legal institutions, failing to support Hypothesis 2. The coefficient on *Visibility* is positive and significant in columns 2 and 3 when AEM is measured by the modified Jones model, indicating that managers decrease AEM in response to air pollution. This result may imply that managers in U.S. firms substitute REM for AEM by decreasing AEM and increasing REM when they are exposed to air pollution. However, the coefficient on Visibility toward AEM is not consistently positive and significant in the analyses of the subsequent sections when AEM is measured by the modified Jones model. It is never significant when AEM is measured by the performance-adjusted modified Jones model.[19] Therefore, we do not claim for the decrease in AEM but maintain a conservative stand that AEM is mostly not affected by air pollution.

In contrast, columns 4 and 5 show that *Visibility* is significantly negatively associated with the extent of REM (coeff. = -0.010, *t*-value = -5.09 in column 4; coeff. = -0.070, *t*-value = -4.99 in column 5). Specifically, a one standard deviation increase in *Visibility* is associated with a 0.017 decrease in REM as shown in column 4 (-0.0104 × 1.653), which equals a 24.3 percent decrease in REM (dep mean: -0.070, 0.017/0.070 × 100 = 24.3%), and a one standard deviation increase in *Visibility* is associated with a 0.116 decrease in REM ranking as reported in column 5 (-0.070 × 1.653) among firms in the same industry in a year, which is equivalent to a 2.6 percent decrease in REM ranking compared to the mean (dep mean: 4.45). These results suggest that polluted air, as characterized by lower visibility, leads to an increase in REM, which is consistent with Hypothesis 1 that air pollution

[19] As shown in Panel E of Table 9, *Visibility* has a positive relation with productivity. To the extent that accounting performance such as ROA is positively correlated with productivity, the significantly positive coefficient on *Visibility* in columns 2 and 3 of Table 5 may be capturing this "performance effect" of AEM. This underscores the importance of adjusting performance when AEM is estimated.

induces managers' myopic decision-making.

Overall, the coefficients on the control variables are consistent with those reported in prior studies. For example, larger firms (*Size*) are less likely to engage in AEM and REM due to their higher level of reporting transparency. Firms audited by Big N auditors (*Big N*) are less likely to engage in both AEM and REM, which resonates with extant literature that high-quality auditors constrain both AEM (Becker et al., 1998; Francis and Wang, 2008) and REM (Choi et al., 2018). Firms with higher institutional ownership (*INST%*) are less likely to conduct AEM, which is consistent with stronger monitoring by institutional investors. Loss firms (*Loss*) are also less likely to conduct both AEM and REM. It seems that highly levered firms (*Leverage*) or low growth potential firms (*BM*) use REM as a substitute for AEM to boost earnings. Consistent with Kasznik (1999) and Kothari et al. (2005), we find that AEM has a positive relation with ROA.[20]

Table 5 About Here.

Focusing on the aggregate measure of REM, we find that exposure to polluted air is associated with a higher degree of REM. This aggregate REM measure consists of three individual REM components – REM_{CFO}, REM_{PROD}, and REM_{DISX}, each of which can represent a unique aspect of REM. Thus, through which specific type of REM activity does air pollution exert this observed influence? We explore this question by regressing REM_{CFO}, REM_{PROD}, and REM_{DISX}, separately, on $Visibility$ using Eq. (1). The results are displayed in Table 6.

Air pollution does not have a significant effect on a firm's discretionary cash flows from operations (REM_{CFO}), as shown in column 1. In contrast, *Visibility* is negatively associated with

[20] In contrast, the coefficient on *ROA* is negative when the dependent variable is *REM* or *REM Rank* as shown in columns 4 and 5. While prior studies report strong empirical evidence for the positive correlation between ROA and AEM, there is no theoretical or empirical evidence for such a consistent relation between ROA and REM. For example, Zang (2012) and Sohn (2016) report mixed results about the relation between ROA and REM across different tables in their papers.

REM_{PROD} as shown in column 3, and negatively associated with REM_{DISX} as shown in column 5, indicating that managers exposed to polluted air increase earnings via overproduction and discretionary expense cuts (coeff. = -0.0030, *t*-value = -3.08 in column 3; coeff. = -0.0078, *t*-value = -5.60 in column 5). A one standard deviation increase in *Visibility* is associated with a decrease in discretionary production costs of 0.0050 (-0.0030 × 1.653), a 21.7 percent decrease compared to its mean of -0.023. By the same token, a one standard deviation increase in *Visibility* is associated with a decrease in discretionary expenditure cuts (or an increase in discretionary expenses) of 0.013 (-0.0078 × 1.653), a 33.3 percent decrease compared to its mean of -0.039. When replacing the levels of these *REM* components with their corresponding decile ranks, the inferences are consistent (see columns 2, 4, and 6). In sum, we find that managers' REM activities in response to air pollution are mainly through overproduction and discretionary expense cuts. The reason for this result, we conjecture, is that manipulating sales prices or credit terms can be easily detected by external monitors such as a firm's auditor, and managers usually do not have good justifications when they are accused of opportunism. In contrast, overproduction or deferment of R&D or advertising investment is more difficult to detect, and managers can justify these practices more easily because production volume and R&D or advertising investment are affected not only by managerial opportunism but also by market demand and competitions.

Table 6 About Here.

5. Cross-sectional Tests

In this section, we explore whether our main findings vary cross-sectionally. The relation between air pollution and REM can be moderated by various levels of external monitoring and corporate governance. On one hand, external monitoring or governance can mitigate the effect of polluted air on REM because stakeholders and regulators can monitor and deter managers' myopic decisions. On the other hand, excessive monitoring or governance may pressure managers to switch from AEM to REM (Ge and Kim, 2014; Ho et al., 2015; Chi et al., 2011; Irani and Oesch, 2016). Moreover, managers are penalized more severely in firms with stronger governance when they miss their performance targets, which can encourage them to engage in more REM (Ding et al., 2021). We proxy for external monitoring using the number of analysts following the firm (*ANAL*), the existence of credit rating (*Credit Rating*), and institutional ownership (*INST%*); and corporate governance using firms' corporate-governance-related CSR score (*CG*), board independence, the percentage of female directors on board, golden parachute, poison pill, and CEO-chairman duality.

5.1. Moderating Effect of External Monitoring

The higher the number of analysts following a firm, the greater the pressure from the external environment.[21] We interact *ANAL* with *Visibility* to examine the moderating effect of analyst following and report the results in Panel A of Table 7. The coefficient on *Visibility*ANAL* is significantly negative in columns 4 and 5, implying that increased REM in response to polluted air is more pronounced among firms with a higher number of analysts following the firms.[22] This finding is consistent with He and Tian (2013) who document that by exerting a lot of pressure on managers to meet short-term goals, analysts impede managers' long-term investment decision-making. Credit rating agencies and institutional investors can also play external monitoring roles. *Ex ante*, it is not clear whether these monitors will pressure firm managers in the same direction as analyst following does, or deter managerial myopia, because different stakeholders have different incentives. While managers are strongly motivated to increase REM to meet analysts' earnings targets, they can

[21] Jing et al. (2022) report that financial analysts serve as external monitors that contribute to the detection and discipline of corporate misbehaviors such as corporate fraud, earnings management, and workplace safety issues.
[22] Interestingly, the coefficient on *Visibility*ANAL* is significantly negative in columns 1 to 3 of Table 7, indicating that the external pressure from analysts to achieve short-term performance induces managers to engage in AEM as well in response to air pollution.

decrease REM if institutional investors and credit rating agencies encourage managers to take actions to maximize long-term firm value. We interact *Credit Rating* and *INST%* with *Visibility* to examine the moderating effect of credit rating agencies and institutional ownership and report the results in Panels B and C of Table 7, respectively. The coefficient on *Visibility*Credit Rating* is significantly positive in columns 4 and 5 of Panel B, and the coefficient on *Visibility*INST%* is significantly positive in column 4 of Panel C, indicating that the REM increase in response to polluted air is mitigated among firms with a credit rating or with higher institutional ownership.

Table 7 About Here.

5.2. Moderating Effect of Corporate Governance

On one hand, managers can conduct more REM after being exposed to polluted air when their firms' corporate governance is weaker because they are less concerned about being detected and punished by the board of directors or other stakeholders. On the other hand, managers can increase REM under strong corporate governance because they can be penalized more severely when missing their performance target in this more stringent monitoring system (Ding et al., 2021). To proxy for the quality of a firm's internal corporate governance, we first use a subcategory of the MSCI KLD data set that is related to the firm's corporate governance (denoted as *CG*). Following Di Giuli et al. (2014) and Cronqvist and Yu (2017), we use the scores for corporate social responsibility (CSR) and the scores for the corporate governance subcategory from MSCI ESG KLD STATS (previously named KLD), which integrates data from multiple sources.[23] Two separate measures are used to assess the quality of the firm's corporate governance: *CG Strength* and *CG Concern*. The higher the magnitude of *CG Strength* (*Concern*), the better (weaker) the internal governance of the firm.

[23] Data sources include macro data at the industry level from academic and NGO data sets, company disclosures (10-K, sustainability report, proxy report, AGM results, and others), government databases, and over 1600 media, NGO, and other stakeholder sources.

In our analysis, we incorporate *CG Strength* or *CG Concern* as primary factors, both independently and in interaction with *Visibility*, the findings of which are presented in Panel A of Table 8. In this table, we do not report the results when the dependent variable is AEM rank or REM rank for brevity but the inferences are the same. Notably, in columns 2, 4, and 6, the coefficient on *Visibility*CG Concern* exhibits a significant negative correlation with both *AEM* and *REM.* This suggests that in instances of deficient corporate governance, air pollution tends to stimulate both accrual-based earnings management and real earnings management. Examining *REM* specifically in columns 5 and 6, we observe significance in the interaction term in column 6 (coefficient = -0.0103, *t*-value = -1.92), suggesting that weaker internal governance amplifies the positive impact of air pollution on *REM*. Intriguingly, this weaker internal governance also prompts firms to engage in higher levels of *AEM*, as evidenced in column 2 (coeff. = -0.0030, *t*-value = -3.02) and column 4 (coeff. = -0.0034, *t*-value = -3.70).

Furthermore, in columns 1 and 3, the coefficient on *Visibility*CG Strength* is positive for both *AEM* measures, with statistical significance in column 1 (when *AEM* is measured using the performance-adjusted modified Jones model). This implies that in situations characterized by robust internal governance, the effect of air pollution on AEM becomes weaker. This finding contributes additional evidence that contrasts with the results of Cho et al. (2022), who observed an increase in accrual-based earnings management in response to air pollution in China. This discrepancy can likely be attributed to the more stringent regulatory oversight and superior corporate governance standards in the U.S. compared to China.

Next, we use board independence (*Board Independence*) and the percentage of female directors on board (*Female Board%)* as our corporate governance variables and report the results in Panel B of Table 8. The coefficient on *Visibility*Board Independence* is positive and significant in column 5 (coeff. = 0.119; t-value = 3.98) and the coefficient on *Visibility*Female Board%* is positive and significant in column 6 (coeff. = 0.020; t-value = 2.29), indicating that better corporate governance mitigates managers' REM-increasing activities in response to air pollution. When we proxy for corporate governance using golden parachute (*G-Parachute*) and poison pill (*Poison Pill*) in Panel C of Table 8, the inference is similar. The coefficient on *Visibility*G-Parachute* is negative and significant in column 5 (coeff. = -0.0187; t-value = -2.01), implying that managers' opportunistic REM in the face of air pollution is exacerbated in poor corporate governance. The coefficient on *Visibility*Poison Pill* is insignificant in column 6. Finally, we use CEO-chairman duality (*Duality*) as an alternative corporate governance variable and report the results in Panel D of Table 8.[24] In columns 5 and 6, the coefficient on *Visibility*Duality* is significant but in the opposite direction, meaning that air pollution-driven REM is alleviated in firms with poor corporate governance. We conjecture that CEO-chairman duality plays its governance role differently in our specific setting: more powerful CEOs might be psychologically less vulnerable to cognitive bias or productivity loss in an environment of air pollution. Throughout Panels B to D, the coefficients on the interaction variables are mostly insignificant in the AEM regressions.

Our study, in conjunction with Cho et al. (2022), provides a comprehensive view of the relationship between air pollution and earnings management behavior. It underscores the influence of corporate governance and regulatory supervision in different settings on this relationship.

Table 8 About Here.

5.3. Knowledge-Intensive vs. Labor-Intensive Industries

If managers of firms located in high air pollution areas engage in more REM due to the effect of air pollution on their cognitive functioning leading them to focus on short-term outcomes, this relation will be more pronounced for firms in knowledge-intensive industries than those in labor-intensive

[24] We construct two different duality measures. *Duality 1* is coded one or zero only for firm-years with non-missing values for KLD strengths and KLD concerns, and all other firm-years are excluded from the sample; *Duality 2* is coded one or zero for all the firm-years regardless of the existence of KLD data.

industries. This is because many aspects of decision-making and business operations depend heavily on sophisticated and complex knowledge and the exchange of ideas in knowledge-intensive firms, so there is more room for air pollution to affect the cognitive functioning of these firms' managers. To test this prediction, we divide our sample into two subsamples based on the level of knowledge intensity or labor intensity and repeat our main analysis for each subsample.

First, we classify our sample firms into knowledge-intensive and non-knowledge-intensive industry subsamples following Von Nordenflycht (2010) and Baldwin and Gellatly (2001) and report the results in Panels A and B of Table 9, respectively. The coefficient on *Visibility* is negative and significant in columns 5 and 6 (where the dependent variable is *REM*) of Panel A for firms in knowledge-intensive industries. On the contrary, the coefficient on *Visibility* is insignificant in column 5 and marginally significant (at the 10% level) in column 6 of Panel B for firms in non-knowledge-intensive industries. Second, we classify our sample firms into labor-intensive and non-labor-intensive industry subsamples following Bhojraj and Oler (2003), Kile and Phillips (2009), and Krishnan and Press (2003) and report the results in Panels C and D of Table 9, respectively. The coefficient on *Visibility* is insignificant in columns 5 and 6 of Panel C for firms in labor-intensive industries. In contrast, the coefficient on *Visibility* is negative and significant in columns 5 and 6 of Panel D for firms in non-labor-intensive industries. In all the panels, the coefficient on *Visibility* is insignificant when the dependent variable is *AEM* measured by the performance-adjusted modified Jones model (or is positively significant when *AEM* is measured by the modified Jones model), consistent with our main results. The results of these cross-sectional tests support our prediction that the effect of polluted air on REM through managers' cognitive functioning is stronger for firms in knowledge-intensive (or less labor-intensive) industries.

Relatedly, to test our proposition that air pollution induces managers to engage in REM through the alternative channel of decreased productivity, we proxy for managers' productivity using TFP

(Total Factor Productivity) following Levinsohn and Petrin (2003) and regress TFP on *Visibility* and control variables. The results are presented in Panel E of Table 9. The coefficient on *Visibility* is positive and significant, supporting our premise that air pollution decreases managers' productivity and thus they engage in REM to compensate for the loss from decreased productivity.

Table 9 About Here.

6. Robustness Checks

6.1. Using Propensity Score Matched Sample

Our findings may be subject to spurious regression concerns due to systematic differences between firms in more polluted and less polluted cities in the sample. To alleviate this concern, we adopt the propensity score matching method. As is shown in Table 4, firms that are located in more polluted regions are usually smaller (*Size*) and older (*Firm Age*), have a lower annual stock return (*RET*), have a lower propensity to report loss (*Loss*), are less likely to belong to a litigious industry (*Litigious*), and have a higher book-to-market ratio (*BM*), return on assets (*ROA*), leverage (*Leverage*), institutional ownership (*INST%*), net operating assets (*NOA*), and propensity to be audited by a Big N auditor (*Big N*). These results indicate systematic differences between firms in cities with more polluted and less polluted air. To address this issue, we divide our sample into high (treated) vs. low *Visibility* (control) subsamples based on the median value of *Visibility* and then implement a PSM model, where the dependent variable is the high *Visibility* subsample indicator and the explanatory variables are the same as the control variables in Eq. (1). We match each observation in the treated subsample to at most three observations with the closest propensity score in the control subsample. We drop pairs in which the absolute difference in propensity scores exceeds 0.03 and are left with 4,128 firm-year observations after matching. The unreported differences between these two subsamples diminish for all the matched variables except for *Leverage*.

Next, we use this matched sample to rerun our baseline model, Eq. (1), and display the results in Table 10. These results are similar to our main results in Table 5. Specifically, the coefficient on *Visibility* is -0.00733 when the dependent variable is the level of REM, which is significant at the 5 percent level (*t*-value = -2.18), and the magnitude is similar to that of the corresponding coefficient in Table 5 (-0.0104). Therefore, it is not likely that our main results are driven by the systematic differences between firms in regions that are exposed to more or less polluted air.

The endogeneity issue is less problematic in our setting because air pollution or the determinants of air pollution are mostly exogenous to managers' earnings management decisions. However, we admit that we cannot fully exclude the possibility for unobserved correlated-omitted variables to affect our main findings. To further address this concern, we use the amendments of the U.S. Clean Air Act during the period 2006-2012 as an exogenous event to affect air pollution.[25] EPA amended the air pollution testing system for motor vehicles in 2006 and implemented new restrictions on NOx emissions from gas turbine aircraft engines in 2012. We construct an indicator variable, *CAA_Amend*, which takes a value of one if a firm-year is in or after 2012, and zero if it is before 2006, and exclude firm-years in 2007-2011. When we use *CAA_Amend* as an alternative test variable for *Visibility*, its coefficient is negative and significant in the REM regressions (untabulated). The results of this additional test further alleviate the endogeneity concern.

Table 10 About Here.

6.2. Coastal and Inland: Environmental Scrutiny

In this section, we examine whether external scrutiny of a firm's environmental practices serves as an alternative channel underlying the main effect. That is, companies operating in areas with air

[25] U.S. Clean Air Act must have affected the level of air pollution in the U.S. with the most prominent test power in 1963 when it was first enacted. However, we cannot use it as an exogenous policy event because it took place long before the start of our sample period.

pollution may face more stringent scrutiny from regulators and stakeholders concerning their environmental practices. The scrutiny could lead firms to incur a higher environment-related cost, worsen financial performance, and result in a higher likelihood of REM. In this section, we use an indicator variable for whether a firm is located in a coastal area to proxy for the level of scrutiny it is exposed to from regulators and stakeholders regarding its environmental practices. The reasons are twofold. First, firms that are located in coastal areas are subject to a higher level of scrutiny because of institutional and regulatory practices in coastal areas.[26] Second, existing regulatory laws are stricter for firms located along coastal areas than they are for firms located inland. Examples of these include the U.S. Coastal Zone Management Program[27] and the Environmental Protection Agency (EPA).[28]

We classify U.S. states into two categories: coastal and inland areas and create an indicator variable for a state being coastal (*Coastal*). The data are obtained from NOAA's official website and Google Maps. We include *Coastal* as a main effect and an interaction with *Visibility* and tabulate the results in Table 11. If stricter regulatory scrutiny is the main cause for REM, the coefficient on this interaction variable will be significantly negative. The results show that the coefficient on *Visibility*Coastal* is insignificant, while the coefficient on *Visibility* is still significantly negative across all columns, suggesting the robustness of our main findings. These results further mitigate the possibility that exposure to polluted air increases a firm's REM by increasing the level of scrutiny regarding the firm's environmental practices.

Table 11 About Here.

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[26] For example, The Nature Conservancy protects coastal communities; The Coastal Protection-Coral Reef Alliance protects biodiversity along the coastal areas; NOAA Office for Coastal Management monitors coastal activities.
[27] Authorized by the Coastal Zone Management Act of 1972, the U.S. Coastal Zone Management Program provides the basis for protecting, restoring, and responsibly developing the nation's diverse coastal communities and resources.
[28] The Environmental Protection Agency (EPA) protects and restores ocean and coastal ecosystems by promoting watershed-based management, preventing aquatic pollution, managing ocean dumping sites, assessing coastal conditions, establishing effective partnerships, and facilitating community-led science-based efforts. These programs increase scrutiny on coastal-area firms from regulators to ensure a clean and safe operating environment that sustains human health, the environment, and the economy.

6.3. Alternative Measures and Specifications

We have shown that *Visibility* is significantly and negatively associated with REM and demonstrate that this effect is moderated by external monitoring and internal corporate governance. One may question whether the results hold if we include additional weather-related variables that may be correlated with, and thus confound the effect of, *Visibility*. To this end, we include them separately and together in Eq. (1): mean temperature, mean dew point, mean sea-level pressure, mean wind speed, maximum sustained wind speed, minimum temperature, and average rain occurrences. We find that the coefficient on *Visibility* is negative and significant after controlling for these additional variables (See Table OA1 in the Online Appendix for details).[29, 30]

In our main and cross-sectional analyses, we adopt *Visibility*, which measures air pollution indirectly, as our test variable instead of using the direct measure of air pollution such as PM 2.5. Our choice is mainly because the existing measure of actual air pollution is vulnerable to data manipulation issues, and *Visibility* is a more accurate measure that is free from this issue. When there are many pollutant particles in the air, they scatter and absorb light, thereby decreasing visibility. Prior studies also prove that visibility is closely related to actual air pollution and people's health (e.g., Thach et al. 2010). In our sample, the correlation between *Visibility* and PM 2.5 is negative and

[29] As for the signs of other weather-related variables, a lower dew point, a higher value of mean wind speed, a higher value of maximum sustained wind speed, a lower value of minimum temperature, and a higher number of rain occurrences are all positively associated with *REM*, which is consistent with the main inference from *Visibility*.

[30] To control for the confounding effect of fog on *Visibility*, our main regression model of Eq. (1) includes the yearly mean of fog occurrences (*Fog*) as a control variable. To address this concern further, we divide our sample into quintiles based on *Fog* and regress Eq. (1) using only the bottom quintile to minimize the effect of fog on visibility. The coefficient on *Visibility* remains negative and significant, indicating that the main inference from this subsample analysis is unaltered (untabulated). We also explore whether our main findings are a result of weather-induced mood because prior studies (e.g., DeHaan et al. 2017) document that even sophisticated market participants, such as analysts, are adversely affected by weather-induced mood. To this end, we divide our sample into terciles based on the yearly mean of cloud cover at the firm's location and repeat our main regression separately for each tercile. The coefficient on *Visibility* is negative and significant in the bottom and middle terciles, implying that our main inference is robust to controlling for managers' weather-induced mood (untabulated). However, the coefficient on *Visibility* is insignificant in the top tercile, hinting the possibility of weather-induced mood effect dominating when the weather is extremely cloudy.

significant (correlation coefficient = -0.394; p-value < 0.01). Nonetheless, *Visibility* can contain noise that is not related to actual air pollution because many factors influence visibility. Moreover, visibility can directly affect corporate activities in ways that are independent of air pollution. For instance, poor visibility can disrupt transportation logistics, supply chain operations, and employee commutes, thereby influencing corporate performance and consequently, earnings management. To address this concern, we regress *Visibility* on PM 2.5 and obtain the fitted value of *Visibility* and the regression residual. We claim that the fitted value of *Visibility* is the air-pollution-related part of *Visibility* whereas the residual is the remaining part of *Visibility* that is not related to air pollution. Therefore, when we regress Eq. (1), the coefficient on the fitted value of *Visibility* (residual) is expected to be negative and significant (insignificant). The results tabulated in Panel A of Table 12 support this prediction. This test mitigates the concern about the construct validity of *Visibility* regarding its ability to capture the level of actual air pollution.

To address this concern further, we replace *Visibility* with the population-weighted annual average level of particulate matter 2.5 (PM 2.5) as the test variable and regress Eq. (1) to see whether our main findings are robust to using a more direct measure of air pollution. The results are summarized in Panel B of Table 12. We find similar results to those in Table 5. While the level of PM 2.5 exerts a null effect on AEM as shown in columns 1 to 3, it has a significantly positive impact on a firm's REM as shown in columns 4 and 5. Specifically, a one standard deviation increase in PM 2.5 is associated with an increase in the level of *REM* of 0.0253 (0.0091 × 2.776), which is equivalent to a 36.1 percent increase relative to the mean (dep mean: -0.070, 0.0253/0.070 × 100 = 36.1%). A one standard deviation increase in PM 2.5 is associated with an increase of 0.223 (0.0804 × 2.776) in the ranking of REM among the firms in the same industry in a year, which is equivalent to a 5.01 percent increase compared to the mean ranking of 4.45.

Table 12 About Here.

Next, we test whether our results are driven by geographical characteristics, which may be correlated with both air pollution and earnings management. Besides including firm-level characteristics, and industry- and year-fixed effects, we further include city-fixed effects in our baseline model. The untabulated results are quantitatively similar to our main results displayed in Tables 5 to 9. Therefore, geographical characteristics are unlikely to be the mechanism through which polluted air positively influences a firm's REM activities.

We have shown that exposure to polluted air during the year prior to a firm's fiscal year-end induces managers to engage in a higher degree of REM but exerts no significant impact on AEM. Finally, as a robustness check, we use each firm's actual period end date ("apdedate" in Compustat) as the reference point and examine the effect of *Visibility* the firm is exposed to during the one-year (and three-month) period prior to the actual end date and during the three-month period after the fiscal year-end on the firm's AEM and REM. Our findings are consistent with our main results as reported in Tables OA2 to OA10 in the Online Appendix, thus corroborating our conclusion that exposure to polluted air is associated with more REM but does not seem to significantly affect AEM.

7. Conclusion

This paper examines how air pollution influences firms' behavior regarding real earnings management (REM). Previous studies have extensively explored the determinants of REM, including capital market pressure, internal and external governance, the stringency of accounting standards, and analyst coverage, but they have largely overlooked external environmental factors. Even when external environmental factors are considered, most studies focus solely on accrual-based earnings management (AEM), with little discussion about REM.

Employing a sample of U.S. firms from 2003 to 2017 and a novel, accurate measure of air pollution, we find that firm managers exposed to prolonged periods of polluted air conduct more

REM but not AEM. This may be because AEM is more easily detectable and is subject to severe penalties in countries with strong legal institutions such as the U.S. (Francis et al., 2016). Furthermore, we find that firms boost their earnings through overproduction and discretionary expense cuts, rather than through excessive sales price discounts or lenient credit terms. In cross-sectional analyses, we also find that the impact of polluted air on increasing REM is amplified when firms face external pressure from analysts. Conversely, this impact is mitigated when firms have a credit rating or high institutional ownership and face internal monitoring due to strong corporate governance. Furthermore, this impact is more pronounced in knowledge-intensive than in labor-intensive industries.

We interpret our main findings as being attributed to managerial myopia and reduced productivity resulting from air pollution. Managerial myopia is a widely recognized and extensively researched phenomenon in the business world (Graham et al., 2005; He and Tian, 2016). Managers and employees exposed to polluted air may experience myopia due to changes in individuals' neuro-cognitive functioning processes (Tzivian et al., 2015), heightened levels of aggressiveness (Berman et al., 2019; Bondy et al., 2020), and hormonal changes that lead individuals to focus on the present (Li et al., 2017; Riis-Vestergaard et al., 2018). As a result, managers of the affected firms may engage in earnings management to maximize short-term financial performance. Furthermore, employees' long-term exposure to polluted air can reduce productivity (Chang et al., 2016, 2019; Lichter et al., 2017). To compensate for the decreased financial performance due to this productivity loss, managers may be motivated to engage in earnings management.

This is the first study to investigate the effect of air pollution on REM, thereby broadening the scope of prior literature on earnings management. REM is influenced by the activities and decisions of both CEOs and other employees who are similarly exposed to polluted air. Furthermore, REM is implemented continuously throughout the year, and air pollution also continuously affects managers' and employees' cognitive functioning and productivity. Therefore, the effect of air pollution can be more prominent on REM than it is on AEM.

By identifying air pollution as a previously unknown factor influencing REM, our study can help accounting regulators improve the quality of financial reporting. We propose that, by improving air quality through cooperation with environmental regulators, accounting regulators can more efficiently achieve their goal of enhancing financial reporting quality.

Finally, despite conducting a range of robustness tests and additional analyses, we acknowledge that our findings may not be entirely free from potential endogeneity issues and concerns about variable measurement errors.

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Table 1: Sample Selection Procedure

Step	Number of observations	Reasons for attrition
1	52,593	————
2	48,332	Each firm-year observation is matched to one (or more) closest station to the firm during the period prior to the firm's fiscal year end. Furthermore, Firm-year observations for which the closest station to the firm was not operating or did not record the weather information over the one year period prior to the firm's fiscal year end date were dropped from the sample.
3	47,662	Among the the 48,332 firm-year observations, 670 observations, for which a firm is matched to multiple stations with equal distance, were dropped from the sample.
4	40,368	5,156 firm-years in financial industry (SIC 6000-6999) and 2,138 firm-years in utilities industry (SIC 4900-4999) are dropped from the sample.
5	11,590	Firm-year observations that were missing values for any of the main dependent variables (AEM, REM, REM_{CFO}, REM_{PROD}, REM_{DISX}, and the corresponding ranks), independent variables (visibility), firm control variables, industry codes, or the fiscal year variable would be dropped from the sample.

Table 2: Summary Statistics of Firm Characteristics

	N	Mean	Std. Dev.	Bottom 25%	Median	Top 25%
AEM (performance-adjusted)	9229	-0.017	0.097	-0.051	-0.011	0.024
AEM (modified Jone's)	11590	-0.014	0.092	-0.045	-0.008	0.026
AEM Rank	11590	4.431	2.871	2.000	4.000	7.000
REM	11590	-0.070	0.423	-0.285	-0.052	0.142
REM Rank	11590	4.452	2.986	2.000	4.000	7.000
REM Variability	11590	0.495	0.332	0.222	0.444	0.778
REM_{CFO}	11590	-0.008	0.115	-0.063	-0.012	0.039
Rank(REM_{CFO})	11590	4.543	2.865	2.000	5.000	7.000
REM_{PROD}	11590	-0.023	0.188	-0.116	-0.010	0.052
Rank(REM_{PROD})	11590	4.429	2.958	2.000	4.000	7.000
REM_{DISX}	11590	-0.039	0.242	-0.143	-0.011	0.076
Rank(REM_{DISX})	11590	4.421	2.996	2.000	4.000	7.000
Size	11590	6.888	1.674	5.730	6.800	7.974
BM	11590	0.582	0.717	0.250	0.435	0.716
ROA	11590	0.022	0.162	-0.005	0.047	0.092
Leverage	11590	0.470	0.214	0.303	0.471	0.625
Firm Age	11590	21.159	15.706	9.000	16.000	29.000
Big N	11590	0.847	0.360	1.000	1.000	1.000
Auditor Tenure	11590	5.923	4.995	2.000	4.000	8.000
Loss	11590	0.264	0.441	0.000	0.000	1.000
Sales	11590	2835.623	6654.437	228.838	733.566	2372.072
Sales Growth	11590	0.520	34.497	-0.010	0.077	0.190
Litigious	11590	0.393	0.488	0.000	0.000	1.000
INST%	11590	0.762	0.234	0.637	0.825	0.958
Credit Rating	11590	0.318	0.466	0.000	0.000	1.000
RET	11590	0.160	0.756	-0.192	0.061	0.347
StdSales	11590	284.865	721.948	22.828	72.786	231.076
NOA	11590	0.248	41.709	-0.082	0.144	0.374
HHI	11590	0.151	0.127	0.077	0.118	0.190
ANAL	11529	9.067	7.256	4.000	7.000	13.000
PM 2.5	3652	10.632	2.776	8.900	10.300	12.500

Notes: This table presents the descriptive statistics for the firm-level variables used in our main analyses. See Appendix A for detailed variable definitions and measurement.

Table 3: Summary Statistics of Weather-Related Characteristics

	N	Mean	Std. Dev.	Bottom 25%	Median	Top 25%
Panel A: Weather Station-Year Level						
Temp.	3921	57.489	8.635	51.245	56.211	63.249
Dew	3913	44.681	8.616	39.277	43.537	49.366
Sea-level Pressure	3242	1016.473	1.981	1015.807	1016.697	1017.488
Visibility	3921	9.133	1.858	8.741	9.060	9.390
Wind	3918	6.151	1.573	5.088	6.114	7.186
Gust	3870	45.911	8.638	40.000	45.100	50.900
Max Wind	3917	31.524	6.860	28.000	31.100	35.900
Total Precip.	3911	4.274	11.293	0.088	0.129	0.569
Snow Depth	3921	0.122	0.400	0.000	0.000	0.016
Max Temp.	3921	97.396	8.942	93.900	97.000	102.000
Min Temp.	3921	9.524	17.011	-2.900	8.100	23.000
Fog	3921	0.107	0.126	0.036	0.077	0.120
Rain	3921	0.312	0.134	0.251	0.336	0.388
Snow	3921	0.071	0.098	0.003	0.044	0.115
Hail	3921	0.001	0.002	0.000	0.000	0.000
Thunder	3921	0.081	0.063	0.025	0.079	0.123
Tornado	3921	0.000	0.001	0.000	0.000	0.000
	N	Mean	Std. Dev.	Bottom 25%	Median	Top 25%
Panel B: Firm-Year Level						
Temp.	11590	57.990	8.107	52.535	57.870	62.321
Dew	11572	44.693	7.728	40.018	44.812	48.737
Sea-level Pressure	9900	1016.402	1.955	1015.867	1016.681	1017.414
Visibility	11590	9.248	1.653	8.793	9.122	9.505
Wind	11587	6.000	1.453	5.018	5.857	6.996
Gust	11432	44.231	8.449	38.100	43.500	49.000
Max Wind	11584	30.278	6.855	26.000	29.900	34.800
Total Precip.	11570	3.151	9.562	0.063	0.122	0.385
Snow Depth	11590	0.108	0.346	0.000	0.000	0.014
Max Temp.	11590	97.632	9.270	95.000	98.100	102.000
Min Temp.	11590	12.430	16.583	0.000	12.000	28.000
Fog	11590	0.100	0.127	0.027	0.066	0.115
Rain	11590	0.289	0.133	0.197	0.313	0.375
Snow	11590	0.063	0.104	0.000	0.027	0.093
Hail	11590	0.001	0.002	0.000	0.000	0.000
Thunder	11590	0.069	0.063	0.003	0.063	0.115
Tornado	11590	0.000	0.001	0.000	0.000	0.000

Notes: This table presents the descriptive statistics for the various weather variables used in our analyses. See Appendix B for detailed variable descriptions.

Table 4: Univariate Test

	All	Polluted	Unpolluted	Polluted-Unpolluted
AEM (performance-adjusted)	-0.017	-0.011	-0.024	0.012***
AEM (modified Jone's)	-0.014	-0.008	-0.019	0.011***
AEM Rank	4.431	4.641	4.222	0.419***
REM	-0.070	-0.026	-0.114	0.088***
REM Rank	4.452	4.804	4.100	0.704***
REM_{CFO}	-0.008	-0.006	-0.010	0.004
Rank(REM_{CFO})	4.543	4.674	4.412	0.262***
REM_{PROD}	-0.023	-0.012	-0.035	0.022***
Rank(REM_{PROD})	4.429	4.676	4.181	0.495***
REM_{DISX}	-0.039	-0.008	-0.069	0.061***
Rank(REM_{DISX})	4.421	4.842	4.000	0.842***
Size	6.888	6.850	6.927	-0.077*
BM	0.582	0.614	0.550	0.065***
ROA	0.022	0.032	0.013	0.018***
Leverage	0.470	0.481	0.459	0.023***
Firm Age	21.159	23.238	19.080	4.158***
Big N	0.847	0.859	0.836	0.023***
Auditor Tenure	5.923	5.966	5.880	0.087
Loss	0.264	0.232	0.297	-0.065***
Sales	2835.623	3190.384	2480.984	709.400***
Sales Growth	0.520	0.148	0.892	-0.745
Litigious	0.393	0.329	0.456	-0.127***
INST%	0.762	0.768	0.755	0.013**
Credit Rating	0.318	0.340	0.295	0.046***
RET	0.160	0.143	0.176	-0.034*
StdSales	284.865	291.959	277.774	14.184
NOA	0.248	1.098	-0.603	1.701*
HHI	0.151	0.151	0.151	-0.000
ANAL	9.067	8.592	9.542	-0.950***
PM 2.5	10.632	11.730	9.065	2.665***
Observations	11590	5794	5796	11590

Notes: This table presents the univariate test results about the difference of various firm characteristics between the firms located in high vs. low air pollution areas. We test the significance of the difference using the t-test. See Appendix A for detailed variable definitions. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Table 5: The Effect of Visibility on Earnings Management

	Accrual Earnings Management			Real Earnings Management	
	(1)	(2)	(3)	(4)	(5)
	AEM (performance-adj.)	AEM (modified Jones)	AEM Rank	REM	REM Rank
Visibility	0.000295	0.00142**	0.0328*	-0.0104***	-0.0700***
	(0.52)	(2.80)	(1.96)	(-5.09)	(-4.99)
Fog	-0.0116	0.0120*	0.258	0.0843**	0.521*
	(-1.60)	(2.13)	(1.20)	(2.88)	(2.48)
Size	-0.00766***	-0.00382***	-0.165***	-0.0455***	-0.371***
	(-4.95)	(-3.47)	(-6.88)	(-10.08)	(-11.33)
BM	-0.00777***	-0.00412**	-0.180***	0.0240*	0.149
	(-3.90)	(-3.26)	(-4.33)	(2.40)	(1.94)
ROA	0.348***	0.258***	3.777***	-0.819***	-5.113***
	(8.08)	(13.22)	(13.73)	(-16.31)	(-17.95)
Leverage	-0.0172**	-0.0182***	-0.467***	0.187***	1.562***
	(-2.84)	(-3.61)	(-3.40)	(9.36)	(11.09)
Firm Age	0.000251***	0.000270***	0.0158***	0.00139***	0.0106***
	(4.63)	(5.86)	(9.15)	(5.83)	(6.00)
Big N	-0.00484	-0.00872**	-0.248**	-0.0489***	-0.380***
	(-1.51)	(-3.07)	(-3.07)	(-4.30)	(-4.76)
Auditor Tenure	-0.000281	-0.000183	-0.0000315	-0.000226	0.00200
	(-1.95)	(-1.42)	(-0.01)	(-0.32)	(0.40)
Loss	-0.00627	-0.0112**	-1.115***	-0.0693***	-0.332***
	(-0.75)	(-2.89)	(-13.53)	(-5.84)	(-4.27)
Sales Growth	-0.00924	-0.00000682	0.00101***	0.0000209	0.0000548
	(-1.58)	(-0.26)	(3.47)	(1.74)	(0.70)
Litigious	0.0137***	0.00177	-0.269*	-0.322***	-1.906***
	(3.69)	(0.53)	(-2.42)	(-17.27)	(-15.61)
INST%	-0.0308***	-0.0180***	-0.810***	-0.0309	0.0216
	(-6.21)	(-4.52)	(-6.51)	(-1.71)	(0.18)
RET	-0.000550	0.000363	-0.0283	-0.00772	-0.00513
	(-0.34)	(0.27)	(-0.70)	(-1.34)	(-0.14)
StdSales	-0.00000145	-0.00000225	-0.0000739	0.0000712***	0.000522***
	(-0.82)	(-1.70)	(-1.61)	(4.78)	(4.59)
NOA	-0.000282	-0.00000771	0.000902*		
	(-1.69)	(-0.23)	(2.15)		
REM	0.0551***	0.0575***	1.663***		
	(13.08)	(16.61)	(22.75)		
HHI				-0.0172	-0.178
				(-0.29)	(-0.40)
AEM				1.247***	7.928***
				(21.22)	(21.95)
Constant	0.0634***	0.0266**	6.514***	0.430***	7.792***
	(5.64)	(3.09)	(26.78)	(10.75)	(27.91)
Year FE	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes
N	9229	11590	11590	11590	11590
Adjusted R-sq	0.35	0.27	0.20	0.26	0.26

Notes: This table presents the main regression results to test our hypotheses on the effect of *Visibility* on AEM and REM. See Appendix A for detailed variable definitions. Numbers in parentheses represent t-statistics calculated based on standard errors clustered at the industry-year level. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Table 6: The Effect of Visibility on Individual REM Measures

	(1) REM_{CFO}	(2) Rank(REM_{CFO})	(3) REM_{PROD}	(4) Rank(REM_{PROD})	(5) REM_{DISX}	(6) Rank(REM_{DISX})
Visibility	0.000381	0.0171	-0.00296**	-0.0486***	-0.00777***	-0.0899***
	(0.75)	(1.16)	(-3.08)	(-3.42)	(-5.60)	(-6.08)
Fog	-0.0224***	-0.354*	0.0260	0.367	0.0807***	0.944***
	(-3.57)	(-2.02)	(1.88)	(1.67)	(4.69)	(4.36)
Size	-0.00297**	-0.277***	-0.0181***	-0.326***	-0.0244***	-0.346***
	(-3.10)	(-10.37)	(-9.28)	(-10.35)	(-9.80)	(-11.74)
BM	0.00229	0.0550	0.0101**	0.134**	0.0117	0.0800
	(1.84)	(1.12)	(2.92)	(2.60)	(1.94)	(1.16)
ROA	-0.528***	-8.416***	-0.345***	-4.486***	0.0538	-0.219
	(-21.79)	(-20.96)	(-12.96)	(-15.48)	(1.33)	(-0.71)
Leverage	0.0448***	1.777***	0.0724***	1.351***	0.0702***	1.119***
	(8.98)	(14.25)	(7.79)	(9.59)	(5.75)	(7.73)
Firm Age	-0.000210***	0.0000182	0.000137	0.00409*	0.00146***	0.0185***
	(-4.05)	(0.01)	(1.25)	(2.21)	(10.49)	(9.98)
Big N	0.0111***	0.320***	-0.00394	-0.142	-0.0560***	-0.674***
	(3.72)	(4.41)	(-0.75)	(-1.79)	(-7.80)	(-7.80)
Auditor Tenure	0.000237	0.00517	0.0000109	-0.000745	-0.000474	-0.00614
	(1.77)	(1.24)	(0.03)	(-0.14)	(-1.25)	(-1.20)
Loss	0.00262	0.882***	-0.0258***	-0.135	-0.0462***	-0.747***
	(0.59)	(10.07)	(-4.47)	(-1.68)	(-5.41)	(-8.64)
Sales Growth	-0.00000874	0.000120	0.0000329*	0.000989***	-0.00000327	-0.000262
	(-1.76)	(0.70)	(2.06)	(4.25)	(-0.22)	(-1.39)
Litigious	-0.0257***	-0.747***	-0.117***	-1.617***	-0.180***	-2.139***
	(-7.31)	(-7.34)	(-13.62)	(-13.14)	(-18.02)	(-17.23)
INST%	0.0380***	1.051***	-0.00478	0.0465	-0.0641***	-0.559***
	(8.11)	(8.87)	(-0.58)	(0.38)	(-5.73)	(-4.43)
RET	-0.000644	-0.0398	0.00248	0.0525	-0.00955*	-0.0599
	(-0.48)	(-1.12)	(1.00)	(1.37)	(-2.35)	(-1.77)
StdSales	0.0000114***	0.000441***	0.0000308***	0.000493***	0.0000290***	0.000373***
	(4.50)	(4.89)	(4.67)	(4.37)	(4.69)	(4.47)
HHI	0.0125	0.0641	-0.0245	-0.332	-0.00524	0.0469
	(0.92)	(0.16)	(-0.92)	(-0.72)	(-0.15)	(0.10)
AEM	0.640***	12.93***	0.282***	4.472***	0.325***	3.514***
	(26.60)	(28.05)	(9.95)	(12.71)	(8.26)	(9.63)
Constant	-0.0213*	4.657***	0.149***	7.110***	0.302***	8.603***
	(-2.30)	(18.70)	(8.56)	(26.94)	(12.45)	(31.85)
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
N	11590	11590	11590	11590	11590	11590
Adjusted R-sq	0.51	0.39	0.17	0.19	0.20	0.21

Notes: This table presents the regression results to test the effect of $Visibility$ on REM using three individual REM measures and their ranks. See Appendix A for detailed variable definitions. Numbers in parentheses represent t-statistics calculated based on standard errors clustered at the industry-year level. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Table 7: The Moderating Effect of External Monitoring on the Relation between Visibility and Earnings Management

	Accrual Earnings Management			Real Earnings Management	
	(1) AEM (performance-adj.)	(2) AEM (modified Jones)	(3) AEM Rank	(4) REM	(5) REM Rank
	Panel A: Number of Analysts Following				
Visibility	0.00169**	0.00215***	0.0594***	-0.00814***	-0.0411**
	(2.20)	(3.00)	(2.75)	(-2.51)	(-1.87)
ANAL	0.000845	0.000504	0.0269*	-0.00498**	-0.0244
	(1.19)	(0.95)	(1.35)	(-1.70)	(-1.25)
Visibility × ANAL	-0.000260***	-0.000215***	-0.00735***	-0.000546**	-0.00531***
	(-3.61)	(-4.02)	(-3.56)	(-1.79)	(-2.66)
Constant	0.0186*	-0.00288	4.990***	0.0352	5.137***
	(1.37)	(-0.27)	(18.52)	(0.73)	(15.38)
Baseline Controls	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes
N	9187	11529	11529	11529	11529
Adjusted R-sq	0.30	0.21	0.13	0.16	0.19
	Panel B: Credit Rating				
Visibility	0.0000691	0.000750*	0.00682	-0.0141***	-0.0914***
	(0.12)	(1.44)	(0.39)	(-6.41)	(-6.19)
Credit Rating	0.0339***	0.0265**	0.288	-0.151***	-0.780*
	(2.44)	(1.66)	(0.60)	(-2.62)	(-1.60)
Visibility × Credit Rating	-0.00259**	-0.00215	-0.0191	0.0240***	0.136***
	(-1.72)	(-1.22)	(-0.36)	(3.82)	(2.55)
Constant	0.0698***	0.0384***	6.167***	0.301***	7.085***
	(6.03)	(4.47)	(26.31)	(7.87)	(26.71)
Baseline Controls	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes
N	9229	11590	11590	11590	11590
Adjusted R-sq	0.29	0.21	0.12	0.15	0.18
	Panel C: Institutional Ownership				
Visibility	-0.000948	-0.000462	-0.0359	-0.0262***	-0.132***
	(-0.44)	(-0.22)	(-0.70)	(-2.76)	(-2.41)
INST%	-0.0430**	-0.0331*	-1.372**	-0.234**	-0.851*
	(-1.74)	(-1.41)	(-2.15)	(-2.26)	(-1.41)
Visibility × INST%	0.000902	0.00125	0.0511	0.0178*	0.0644
	(0.34)	(0.50)	(0.76)	(1.61)	(1.00)
Constant	0.0816***	0.0496***	6.730***	0.373***	7.124***
	(3.94)	(2.50)	(13.47)	(4.03)	(13.07)
Baseline Controls	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes
N	9229	11590	11590	11590	11590
Adjusted R-sq	0.30	0.21	0.13	0.15	0.18

Notes: This table presents the regression results to test the moderating effect of the degree of external monitoring on the relation between Visibility and AEM/REM. See Appendix A for detailed variable definitions. The measures for external monitoring in Panel A-C are: the number of analysts following, an indicator for whether a firm has a credit rating, and percentage of institutional ownership, respectively. Numbers in parentheses represent t-statistics calculated based on standard errors clustered at the industry-year level. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Table 8: The Moderating Effect of Corporate Governance on the Relation between Visibility and Earnings Management

	Accrual Earnings Management				Real Earnings Management	
	(1) AEM (performance-adj.)	(2) AEM (performance-adj.)	(3) AEM (modified Jones)	(4) AEM (modified Jones)	(5) REM	(6) REM
	Panel A: CG = CG Strengths and Concerns					
Visibility	-0.000444	0.00113**	0.000718	0.00204***	-0.00497*	-0.00288
	(-0.71)	(1.92)	(1.06)	(3.37)	(-1.56)	(-0.93)
CG Strengths	-0.0188***		-0.00556		0.0446	
	(-2.36)		(-0.60)		(1.15)	
Visibility × CG Strengths	0.00264***		0.00110		-0.00400	
	(3.21)		(1.14)		(-1.04)	
CG Concerns		0.0244***		0.0268***		0.0946**
		(2.57)		(3.12)		(1.89)
Visibility × CG Concerns		-0.00303***		-0.00342***		-0.0103**
		(-3.02)		(-3.70)		(-1.92)
Constant	0.0484***	0.0326***	0.0232***	0.00839	0.00177	-0.0176
	(4.50)	(3.19)	(2.41)	(0.91)	(0.04)	(-0.38)
Baseline Controls	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
N	5490	5490	6181	6181	6181	6181
Adjusted R-sq	0.34	0.34	0.25	0.25	0.19	0.19
	Panel B: CG = Board Independence or Female Board%					
Visibility	0.0108**	0.00149*	0.00925*	0.00226***	-0.0984***	-0.0182***
	(1.83)	(1.55)	(1.38)	(2.49)	(-4.32)	(-4.06)
Board Ind.	0.142**		0.105*		-1.209***	
	(1.95)		(1.30)		(-4.37)	
Visibility × Board Ind.	-0.0152**		-0.0116*		0.119***	
	(-1.92)		(-1.31)		(3.98)	
Female Board%		0.0580***		0.0488***		-0.202***
		(2.79)		(3.14)		(-2.48)
Visibility × Female Board%		-0.00562***		-0.00485***		0.0203**
		(-2.48)		(-2.90)		(2.29)
Constant	-0.0665	0.0222**	-0.0570	0.00787	1.147***	0.344***
	(-1.20)	(1.67)	(-0.93)	(0.68)	(5.13)	(4.96)
Baseline Controls	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
N	4454	4454	5206	5206	5206	5206
Adjusted R-sq	0.46	0.46	0.34	0.34	0.32	0.32

	Accrual Earnings Management				Real Earnings Management	
	(1)	(2)	(3)	(4)	(5)	(6)
	AEM (performance-adj.)	AEM (performance-adj.)	AEM (modified Jones)	AEM (modified Jones)	REM	REM
			Panel C: CG = Golden Parachute or Poison Pill			
Visibility	-0.00280	-0.00236**	-0.00197	-0.00101	0.00312	-0.0116
	(-1.86)	(-2.64)	(-1.68)	(-1.27)	(0.40)	(-1.89)
Golden Parachute	-0.00153		-0.0138		0.112	
	(-0.08)		(-0.87)		(1.28)	
Visibility × Golden Parachute	-0.000335		0.000801		-0.0187*	
	(-0.17)		(0.47)		(-2.01)	
Poison Pill		0.0359		0.0182		-0.215
		(0.82)		(0.55)		(-1.91)
Visibility × Poison Pill		-0.00368		-0.00193		0.0195
		(-0.77)		(-0.53)		(1.59)
Constant	0.0238	0.0156	0.0192	0.00565	-0.0285	0.0823
	(1.39)	(1.27)	(1.34)	(0.50)	(-0.30)	(0.99)
Baseline Controls	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
N	3381	3381	3658	3658	3658	3658
Adjusted R-sq	0.41	0.41	0.30	0.30	0.19	0.19
	Duality 1	Duality 2	Duality 1	Duality 2	Duality 1	Duality 2
			Panel D: CG = CEO-Chairman Duality			
Visibility	0.00224*	0.000583	0.00278**	0.00144**	-0.0403***	-0.0154***
	(1.59)	(0.71)	(1.96)	(2.07)	(-7.46)	(-4.55)
CEO duality	0.0348***		0.0272**		-0.373***	
	(2.38)		(1.92)		(-6.83)	
Visibility × CEO duality	-0.00366**		-0.00283**		0.0426***	
	(-2.32)		(-1.84)		(7.29)	
CEO-Chairman Duality		0.00536		0.00742		-0.0952**
		(0.43)		(0.70)		(-1.96)
Visibility × CEO-Chairman Duality		-0.000592		-0.000969		0.0125***
		(-0.44)		(-0.85)		(2.41)
Constant	0.0121	0.0734***	0.00101	0.0369***	0.549***	0.489***
	(0.73)	(6.67)	(0.07)	(4.00)	(7.09)	(10.36)
Baseline Controls	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
N	4454	7064	5206	8778	5206	8778
Adjusted R-sq	0.46	0.35	0.34	0.28	0.32	0.28

Notes: This table presents the regression results to test the moderating effect of corporate governance on the relation between Visibility and AEM/REM. We use CG Strengths and CG Concerns in Panel A, Board Independence and Female Ratio on Boards in Panel B, Golden Parachute and Poison Pill in Panel C, and CEO-Chairman Duality in Panel D, respectively, as the proxy for corporate governance. See Appendix A for detailed variable definitions. Numbers in parentheses represent t-statistics calculated based on standard errors clustered at the industry-year level. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Table 9: The Effect of Visibility on Earnings Management: Knowledge-Intensive vs. Labor-Intensive Industries

	Accrual Earnings Management			Real Earnings Management	
	(1)	(2)	(3)	(4)	(5)
	AEM (performance-adj.)	AEM (modified Jones)	AEM Rank	REM	REM Rank
	Panel A: Knowledge-Intensive Industries Subsample				
Visibility	0.000670	0.00251**	0.0394	-0.0148***	-0.0876***
	(0.74)	(2.81)	(1.64)	(-4.55)	(-4.09)
Baseline Controls					
Year FE	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes
N	3327	4226	4226	4226	4226
Adjusted R-sq	0.36	0.30	0.24	0.29	0.28
	Panel B: Non-Knowledge-Intensive Industries Subsample				
Visibility	0.000233	0.000757	0.0334	-0.00444	-0.0417*
	(0.32)	(1.28)	(1.45)	(-1.45)	(-1.96)
Baseline Controls					
Year FE	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes
N	5902	7364	7364	7364	7364
Adjusted R-sq	0.36	0.28	0.18	0.24	0.25

	Accrual Earnings Management			Real Earnings Management	
	(1)	(2)	(3)	(4)	(5)
	AEM (performance-adj.)	AEM (modified Jones)	AEM Rank	REM	REM Rank
	Panel C: Labor-Intensive Industries Subsample				
Visibility	-0.000143	-0.00508	-0.0873	0.0220	0.0927
	(-0.07)	(-1.56)	(-1.15)	(1.34)	(1.10)
Baseline Controls					
Year FE	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes
N	1515	1884	1884	1884	1884
Adjusted R-sq	0.25	0.19	0.11	0.16	0.16
	Panel D: Non-Labor-Intensive Industries Subsample				
Visibility	0.000310	0.00168***	0.0396*	-0.0112***	-0.0731***
	(0.53)	(3.29)	(2.34)	(-5.60)	(-5.20)
Baseline Controls					
Year FE	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes
N	7714	9706	9706	9706	9706
Adjusted R-sq	0.37	0.28	0.22	0.28	0.29

	(1)
	Panel E: The Effect of Visibility on Managers' Productivity
Visibility	0.00214**
	(1.91)
Fog	-0.00620
	(-0.26)
Size	-0.172***
	(-25.21)
BM	-0.116***
	(-5.06)
ROA	0.0354*
	(1.43)
Leverage	-0.377***
	(-29.91)
Firm Age	-0.00504***
	(-16.54)
HHI	-0.0520
	(-1.03)
Loss	0.00602
	(0.88)
Sales Growth	0.00000922
	(0.99)
INST%	0.151***
	(9.74)
Constant	3.618***
	(69.66)
Year FE	Yes
Industry FE	Yes
N	11529
Adjusted R-sq	0

Notes: Panels A to D of this table present the regression results to test the effect of $Visibility$ on AEM and REM using subsamples. Our sample is divided into two subsamples based on knowledge-intensive vs. non-knowledge-intensive industries in Panels A and B, and based on labor-intensive vs. non-labor-intensive industries in Panels C and D. Panel E presents the regression results to test the effect of $Visibility$ on Total Factor Productivity. See Appendix A for detailed variable definitions. Numbers in parentheses represent t-statistics calculated based on standard errors clustered at the industry-year level. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Table 10: Propensity Score Matching Sample

	Accrual Earnings Management			Real Earnings Management	
	(1)	(2)	(3)	(4)	(5)
	AEM (performance-adj.)	AEM (modified Jones)	AEM Rank	REM	REM Rank
Visibility	-0.000420	0.000379	0.0117	-0.00733**	-0.0233
	(-0.61)	(0.54)	(0.47)	(-2.18)	(-0.90)
Fog	-0.00801	0.0117*	0.145	0.0724**	0.280
	(-0.72)	(1.41)	(0.41)	(1.71)	(0.85)
Size	-0.0102***	-0.00686***	-0.230***	-0.0476***	-0.327***
	(-6.73)	(-5.62)	(-5.24)	(-6.54)	(-5.85)
BM	-0.00714***	-0.00210	-0.130**	0.0297***	0.224***
	(-3.12)	(-1.00)	(-1.69)	(2.95)	(3.26)
ROA	0.479***	0.389***	7.364***	-0.997***	-6.410***
	(12.49)	(11.36)	(12.27)	(-8.89)	(-8.89)
Leverage	0.00571	-0.00145	-0.227	0.172***	1.412***
	(0.32)	(-0.20)	(-0.91)	(4.92)	(5.61)
Firm Age	0.000196**	0.000290***	0.0161***	0.00256***	0.0118***
	(1.74)	(2.76)	(4.02)	(4.60)	(2.91)
Big N	-0.00175	-0.00223	0.0427	-0.0654***	-0.687***
	(-0.30)	(-0.43)	(0.24)	(-2.73)	(-3.99)
Auditor Tenure	0.000129	-0.0000489	-0.00245	0.00120	0.00888
	(0.67)	(-0.28)	(-0.33)	(1.17)	(1.11)
Loss	-0.00125	-0.00130	-0.858***	-0.101***	-0.445***
	(-0.23)	(-0.26)	(-6.03)	(-5.30)	(-3.30)
Sales Growth	-0.0287**	-0.0174**	-0.339**	0.0339***	0.220**
	(-2.04)	(-1.82)	(-1.72)	(2.56)	(1.81)
Litigious	0.0249***	0.00105	-0.114	-0.303***	-1.838***
	(4.53)	(0.22)	(-0.62)	(-10.16)	(-9.63)
INST%	-0.0284***	-0.0245***	-0.859***	-0.0604**	0.119
	(-3.87)	(-3.97)	(-3.95)	(-1.84)	(0.54)
RET	0.000322	0.00162*	0.00160	-0.00667	-0.0146
	(0.24)	(1.36)	(0.03)	(-0.77)	(-0.25)
StdSales	0.00000194	0.000000171	-0.00000493	0.0000488***	0.000393***
	(0.95)	(0.13)	(-0.09)	(2.66)	(2.57)
NOA	0.00316	0.000435***	0.00446		
	(0.36)	(2.90)	(0.85)		
REM	0.0370***	0.0344***	1.288***		
	(8.86)	(9.03)	(9.58)		
HHI				-0.131*	-1.002*
				(-1.54)	(-1.43)
AEM (modified Jone's)				0.939***	7.498***
				(9.44)	(11.43)
Constant	0.0600***	0.0376***	6.581***	0.440***	7.520***
	(4.19)	(3.60)	(16.79)	(7.04)	(17.43)
Year FE	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes
N	3395	4128	4128	4128	4128
Adjusted R-sq	0.34	0.26	0.16	0.22	0.24

Notes: This table presents the main regression results to test our hypotheses on the effect of Visibility on AEM and REM using the Propensity Score Matched sample. See Appendix A for detailed variable definitions. Numbers in parentheses represent t-statistics calculated based on standard errors clustered at the industry-year level. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Table 11: The Effect of Visibility on Earnings Management: Coastal vs. Inland Regions

	Real Earnings Management			Rank of Real Earnings Management		
	(1)	(2)	(3)	(4)	(5)	(6)
Visibility	-0.0104***	-0.00821***	-0.00558*	-0.0700***	-0.0549***	-0.0536***
	(-5.09)	(-4.04)	(-2.36)	(-4.99)	(-3.80)	(-3.65)
Coastal		-0.0772***	-0.0226		-0.544***	-0.517
		(-9.96)	(-0.56)		(-10.04)	(-1.83)
Visibility × Coastal			-0.00586			-0.00292
			(-1.38)			(-0.10)
Constant	0.430***	0.442***	0.419***	7.792***	7.879***	7.867***
	(10.75)	(11.09)	(10.38)	(27.91)	(28.11)	(28.59)
Baseline Controls	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
N	11590	11590	11590	11590	11590	11590
Adjusted R-sq	0.26	0.26	0.26	0.26	0.27	0.27

Notes: This table presents the regression results to test the difference between coastal and inland areas in the effect of *Visibility* on REM. See Appendix A for detailed variable definitions. Numbers in parentheses represent t-statistics calculated based on standard errors clustered at the industry-year level. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Table 12: The Effect of Visibility on Earnings Management: Using Actual Air Pollution Measures

	Accrual Earnings Management			Real Earnings Management	
	AEM (performance -adj.)	AEM (modified Jones)	AEM Rank	REM	REM Rank
	Panel A: Using Visibility Explained by PM 2.5 and Residual				
Fitted visibility	-0.00489	-0.00311	-0.0288	-0.0678***	-0.601***
	(-0.96)	(-0.74)	(-0.19)	(-3.32)	(-3.88)
Baseline Controls	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes
N	2910	3651	3651	3651	3651
Adjusted R-sq	0.35	0.28	0.17	0.30	0.29
Residual Visibility	-0.00371*	-0.000785	-0.0744	0.00258	0.0430
	(-2.18)	(-0.63)	(-1.31)	(0.43)	(0.91)
Baseline Controls	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes
N	2910	3651	3651	3651	3651
Adjusted R-sq	0.35	0.27	0.17	0.30	0.29
	Panel B: Using PM 2.5 Instead of Visibility				
PM 2.5 (Weighted Annual Mean)	0.000556	0.000358	0.00108	0.00907***	0.0804***
	(0.80)	(0.63)	(0.05)	(3.32)	(3.88)
Baseline Controls	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes
N	2910	3651	3651	3651	3651
Adjusted R-sq	0.35	0.27	0.17	0.30	0.29

Notes: This table presents the regression results to test the effect of unpleasant air quality on AEM and REM using actual air pollution measures. We use the fitted value of $Visibility$ and the residual from the regression of $Visibilty$ on PM 2.5 in Panel A, and use PM 2.5 in Panel B, respectively, as the main test variable. See Appendix A for detailed variable definitions. Numbers in parentheses represent t-statistics calculated based on standard errors clustered at the industry-year level. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Appendix A Descriptions of Firm-Level Variables

Variables	Variable Descriptions
Outcomes	
AEM (performance-adjusted)	Signed discretionary accruals, which are computed using the performance adjusted modified Jones model as in Kothari et al. (2005).
AEM (modified Jones)	Signed discretionary accruals, which are computed using the modified Jones model as in Dechow et al. (1995).
REM	The aggregate measure of real earnings management, which is calculated as the sum of REM_{CFO}, REM_{PROD}, and REM_{DISX} estimated from (Roychowdhury, 2006) regressions; REM_{CFO} and REM_{DISX} are the negative values of abnormal discretionary cash flows and abnormal discretionary expenses, respectively.
AEM Rank	The rank of firm's AEM for the year and industry calculated following Dechow et al. (1995). It is the decile the firm's AEM falls into among all firms of the industry in the year. The higher the AEM, the higher the AEM rank.
REM Rank	The rank of firm's REM for the year and industry. It is the decile the firm's REM falls into among all firms of the industry in the year. The higher the REM, the higher the REM rank.
REM_{CFO}	Negative Discretionary Cash Flows: Negative value of abnormal cash flow from operations, which is measured as the negative value of the deviation of the firm's actual discretionary cash flows from the normal level of discretionary cash flows as are predicted using the corresponding industry-year regression. A higher value represents a higher extent that the firm conducts REM through cutting operating cash flows.
REM_{PROD}	Abnormal production cost, which is measured as the deviation of the firm's actual production costs from the normal level of production costs as are predicted using the corresponding industry-year regression. A higher value represents a higher extent that the firm's production costs are abnormal.
REM_{DISX}	Negative Discretionary Expense: Negative value of abnormal discretionary expenses, which are measured as the negative value of the deviation of the firm's actual discretionary expenses from the normal level of discretionary expenses as are predicted using the corresponding industry-year regression. A higher value represents a higher extent that the firm conducts REM through cutting expenditures.
Firm-level Variables	
Size	Firm size, which is calculated as the logged value of total assets (AT) in the current fiscal year.

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Variables	Variable Descriptions
BM	The book-to-market ratio in the current fiscal year, which is defined as the ratio of a firm's book value of equity (CEQ) and its market value of equity (CSHO $\times$ $PRCC_F$).
ROA	The ratio between a firm's income before extraordinary items ("IB") and its total assets ("AT").
Leverage	The leverage ratio in the current fiscal year, which is defined as the ratio between the firm's total liabilities ($AT-CEQ$) and the firm's total assets (AT).
Firm Age	The age of the firm, which is defined as the number of years starting from the time when the firm's stock returns are first reported in the monthly stock files of the Center for Research in Security Prices (CRSP).
Big N	Indicator (1 = yes, 0 = no) if the firm is audited by a Big N CPA firm, and 0 otherwise.
Auditor Tenure	The number of years firm was audited by the same auditor.
NOA	The ratio between the firm's net operating assets at the beginning of the year and the firm's lagged sales, where the firm's net operating assets are calculated as shareholders' equity less cash and marketable securities, plus total debt).
Sales	The sales of the firm for the current fiscal year.
Loss	Loss indicator that takes a value of one if a firm reports negative net income in year t, and zero otherwise.
Litigious	Litigious industry indicator that takes a value of one if a firm belongs to biotech (SIC code 2833-2836 and 8731-8734), computer (3570-3577, 7370-7374), electronics (3600-3674), or retailing (5200-5961), and zero otherwise.
INST%	The percent of shares outstanding that is owned by institutional owners.
RET	The return to a firm's stocks.
StdSales	The 3-year rolling standard deviation of a firm's sales.
Sales Growth	The annual growth in a firm's sales(revenue).
HHI	The Herfindahl-Hirschman Index (HHI) is a commonly used measure of market concentration. It is calculated by summing the squares of the market shares of all firms in the market. The HHI takes into account the relative size and distribution of the firms in a market and approaches zero when a market consists of a large number of firms of relatively equal size. The HHI increases both as the number of firms in the market decreases and as the disparity in size between those firms increases.
ANAL	The number of analysts following the firm in the current fiscal year, which is obtained from I/B/E/S.
CG Strength	The strength score in corporate governance category from MSCI KLD STAT.
CG Concern	The concern score in corporate governance category from MSCI KLD STAT.

Continued on next page

Variables	Variable Descriptions
Board Ind.	The board independence proxy, which indicates the percentage of independent board members and constitutes a proxy for corporate governance level.
Female Board%	The female board member percentage level, which constitutes a proxy for corporate governance level.
G-Parachute	An indicator that indicate if there is a severance agreement that provides benefits to management or board members in the event of firing, demotion, or resignation following a change in control.
Poison pill	An indicator that indicate if there is a shareholder right that is triggered in the event of an unauthorized change in control that typically renders the target company financially unattractive or dilutes the voting power of the acquirer.
Duality	An indicator indicate if the CEO and the Chairman of a firm is the same person.
Knowledge intensive industry	The classification of knowledge-intensive industries using SIC codes includes sectors such as biotechnology, electronics, information technology, and finance. These industries are characterized by their heavy reliance on the intellectual capabilities of their workforce, significant investments in research and development (R&D), and the application of advanced technologies.
Labor intensive industry	The classification of labor-intensive industries using SIC codes includes sectors such as textiles, agriculture, construction, and certain types of manufacturing that do not require advanced technology. These industries are characterized by their reliance on a large workforce to produce goods or services.
Coastal	An indicator of whether the firm is located in a coastal area of the U.S.

Appendix B Descriptions of Weather-Related Variables

Variables	Variable Descriptions
Temp.	Mean temperature for the day in degrees Fahrenheit.
Dew	Mean dew point for the day in degrees Fahrenheit to tenths.
Sea-level Pressure	Mean sea level pressure for the day in millibars to tenths.
Visibility	Mean visibility for the day in miles to tenths.
Wind	Mean wind speed for the day in knots to tenths.
Max Wind	Maximum sustained wind speed reported for the day in knots to tenths.
Min Temp.	Minimum temperature reported during the day in Fahrenheit to tenths – time of min temp report varies by country and region, so this will sometimes not be the min for the calendar day.
Fog	Indicator (1 = yes, 0 = no/not reported) for the occurrence during the day of fog.
Rain	Indicator (1 = yes, 0 = no/not reported) for the occurrence during the day of rain or drizzle.
Thunder	Indicator (1 = yes, 0 = no/not reported) for the occurrence during the day of thunder.
Gust	Maximum wind gust reported for the day in knots to tenths.
Max Temp.	Maximum temperature reported during the day in Fahrenheit to tenths – time of max temp report varies by country and region, so this will sometimes not be the max for the calendar day.
Total Precip.	Total precipitation (rain and/or melted snow) reported during the day in inches and hundredths; will usually not end with the midnight observation – i.e., may include latter part of previous day.
Snow Depth	Snow depth in inches to tenths – last report for the day if reported more than once.
Snow	Indicator (1 = yes, 0 = no/not reported) for the occurrence during the day of snow or ice pellets.
Hail	Indicator (1 = yes, 0 = no/not reported) for the occurrence during the day of hail.
Tornado	Indicator (1 = yes, 0 = no/not reported) for the occurrence during the day of tornado or funnel cloud.
PM 2.5	The weighted annual mean of PM 2.5 for each city and year.

Appendix C Measurement of AEM and REM

1 Measurement of Accrual-based Earnings Management (AEM)

To measure AEM, we use both the modified Jones model proposed by Dechow et al. (1995) and the performance-adjusted modified Jones model proposed by Kothari et al. (2005).

To make our results comparable to Cho et al. (2022), we first use the modified Jones model proposed by Dechow et al. (1995). We regress the following modified Jones (1991) model by industry (2-digit SIC)-year to estimate the coefficients necessary to compute normal accruals (equation 1).

$$\frac{TA_{it}}{Assets_{i,t-1}} = \alpha_0 + \alpha_1 \frac{1}{Assets_{i,t-1}} + \alpha_2 \frac{\Delta SALES_{i,t}}{Assets_{i,t-1}} + \alpha_3 \frac{PPE_{i,t}}{Assets_{i,t-1}} + \epsilon_{i,t} \tag{1}$$

In the context of the fiscal year t and firm i, we define TA_{it} as firm i's total accruals, calculated as the difference between income before extraordinary items (IB_{it}) and operating cash flows from continuing operations ($OANCF_{it}$), formally expressed as $TA_{it} = IB_{it} - OANCF_{it}$. Both IB_{it} and $OANCF_{it}$ are extracted from firm i's statement of cash flows. Additionally, $Assets_{i,t-1}$ represents firm i's total assets, $\Delta SALES_{i,t}$ denotes the change in revenues from the preceding year, and $PPE_{i,t}$ represents the gross value of property, plant, and equipment.

The coefficients estimated using Equation (1) are then used to calculate firm-specific normal accruals (NA_{it}), and the estimation equation can be seen in Equation (2).

$$NA_{i,t} = \hat{\alpha_0} + \hat{\alpha_1} \frac{1}{Assets_{i,t-1}} + \hat{\alpha_2} \frac{\Delta SALES_{i,t}}{Assets_{i,t-1}} + \hat{\alpha_3} \frac{PPE_{i,t}}{Assets_{i,t-1}} \tag{2}$$

Given the actual accruals calculated in Equation (1) and the normal accruals predicted in Equation (2), our measure of discretionary accruals is computed by taking the difference between the two. Formally, $AEM_{i,t} = (TA_{i,t}/Asset_{i,t-1}) - NA_{i,t}$.

Alternatively, we report the results using the AEM measure following the Kothari et al. (2005) model, namely, the performance-adjusted modified Jones model (AEM (performance-adjusted)). Specifically, we calculate the expected accruals for each focal firm by matching it with another firm in the same industry-year that has the closest lagged value of return on assets (ROA), and subtracting this matched firm's modified Jones model discretionary accruals from the focal firm's modified Jones model discretionary accruals.

2 Measurement of Real Earnings Management (REM)

To estimate abnormal cash flows from operations (CFO), we first regress the actual level of CFO on sales and change in sales using the linear model specified in Equation (3). The residual from this regression is abnormal CFO. We multiply -1 to this value to arrive at REM_{CFO}, our first component of REM.

$$\frac{CFO_{j,t}}{Assets_{j,t-1}} = \alpha_1 \frac{1}{Assets_{j,t-1}} + \alpha_2 \frac{SALES_{j,t}}{Assets_{j,t-1}} + \alpha_3 \frac{\Delta SALES_{j,t}}{Assets_{j,t-1}} + \epsilon_{j,t} \tag{3}$$

In this equation, $CFO_{j,t}$ represents cash flows from continuing operations ($OANCF_{j,t}$), $Sales_{j,t}$ signifies the level of sales, and $\Delta Sales_{j,t}$ represents the change in sales ($SALE_{j,t}$).

Additionally, $Assets_{j,t-1}$ denotes the total assets of firm j in year $t-1$.

In order to estimate the abnormal level of production costs ($PROD$), we initially perform a regression of the actual level of $PROD$ on sales and changes in sales in current and lagged years. This regression employs the linear model defined in Equation (4) for each industry-year combination. Here, production costs ($PROD$) compromises the sum of cost of goods sold ($COGS$) and change in inventory (ΔINV). Subsequently, the residual derived from this regression represents abnormal production costs (REM_{PROD}), which constitutes the second component of REM.

$$\frac{PROD_{j,t}}{Assets_{j,t-1}} = \alpha_1 \frac{1}{Assets_{j,t-1}} + \alpha_2 \frac{SALES_{j,t}}{Assets_{j,t-1}} + \alpha_3 \frac{\Delta SALES_{j,t}}{Assets_{j,t-1}} + \alpha_4 \frac{\Delta SALES_{j,t-1}}{Assets_{j,t-1}} + \epsilon_{j,t} \tag{4}$$

To estimate abnormal discretionary expenses ($DISX$), we first regress the actual level of $DISX$ on change in lagged sales using the linear model specified in Equation (5) for each industry-year. The residual from this regression is abnormal $DISX$. We multiply this value by -1 to obtain REM_{DISX}, which is our third component of REM.

$$\frac{DIScE_{j,t}}{Assets_{j,t-1}} = \alpha_1 \frac{1}{Assets_{j,t-1}} + \alpha_2 \frac{SALES_{j,t-1}}{Assets_{j,t-1}} + \epsilon_{j,t} \tag{5}$$

Where, $DiscE_{j,t}$ is the sum of advertising ($XAD_{j,t}$), $R\&D(XRD_{j,t})$, and selling, general and administrative expenses ($XSGA_{j,t}$) of firm j in year t.

The aggregate measure of real earnings management (REM) is the sum of these three individual components, i.e., $REM = REM_{CFO} + REM_{PROD} + REM_{DISX}$.

Appendix D Correlation Matrix

Variables	AEM (performance-adjusted)	AEM	REM	Size	BM	ROA	Leverage	Firm Age	Big N	Auditor Tenure	Loss	Sales Growth	Litigious	INST%	RET	StdSales	NOA	HHI index	ANAL
AEM (performance-adjusted)	1.000																		
AEM	0.896	1.000																	
	(0.000)																		
REM	0.188	0.208	1.000																
	(0.000)	(0.000)																	
Size	-0.013	-0.007	-0.175	1.000															
	(0.231)	(0.484)	(0.000)																
BM	-0.014	-0.001	0.140	-0.367	1.000														
	(0.191)	(0.883)	(0.000)	(0.000)															
ROA	0.451	0.404	-0.148	0.263	-0.061	1.000													
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)														
Leverage	-0.063	-0.055	0.133	0.186	-0.020	-0.048	1.000												
	(0.000)	(0.000)	(0.000)	(0.000)	(0.045)	(0.000)													
Firm Age	0.117	0.107	0.093	0.322	0.009	0.158	0.158	1.000											
	(0.000)	(0.000)	(0.000)	(0.000)	(0.344)	(0.000)	(0.000)												
Big N	-0.062	-0.066	-0.097	0.348	-0.085	0.072	0.135	0.098	1.000										
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)											
Auditor Tenure	0.012	0.029	-0.027	0.191	-0.015	0.114	0.031	0.181	0.123	1.000									
	(0.277)	(0.004)	(0.006)	(0.000)	(0.130)	(0.000)	(0.002)	(0.000)	(0.000)										
Loss	-0.315	-0.301	0.051	-0.324	0.114	-0.653	0.013	-0.196	-0.103	-0.123	1.000								
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.202)	(0.000)	(0.000)	(0.000)									
Sales Growth	0.003	-0.004	-0.002	0.010	-0.005	-0.004	0.005	-0.013	0.003	-0.012	0.017	1.000							
	(0.742)	(0.694)	(0.863)	(0.310)	(0.589)	(0.654)	(0.631)	(0.170)	(0.737)	(0.225)	(0.076)								
Litigious	-0.128	-0.121	-0.211	-0.045	-0.092	-0.127	-0.219	-0.233	-0.022	-0.032	0.127	-0.006	1.000						
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.025)	(0.001)	(0.000)	(0.556)							
INST%	-0.039	-0.031	-0.126	0.170	0.021	0.164	0.009	0.137	0.177	0.137	-0.187	-0.003	-0.000	1.000					
	(0.000)	(0.002)	(0.000)	(0.000)	(0.030)	(0.000)	(0.379)	(0.000)	(0.000)	(0.000)	(0.000)	(0.770)	(0.983)						
RET	0.046	0.047	-0.035	0.085	-0.139	0.098	0.021	0.000	0.011	0.004	-0.105	-0.003	-0.002	0.007	1.000				
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.033)	(0.965)	(0.262)	(0.685)	(0.000)	(0.749)	(0.803)	(0.483)					
StdSales	0.014	0.020	0.058	0.429	-0.001	0.097	0.176	0.263	0.134	0.092	-0.116	0.001	-0.077	0.030	-0.002	1.000			
	(0.192)	(0.040)	(0.000)	(0.000)	(0.918)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.910)	(0.000)	(0.002)	(0.803)				
NOA	-0.035	0.004	-0.005	-0.022	0.003	0.004	-0.013	-0.004	-0.025	-0.005	0.003	-0.501	0.011	-0.015	-0.005	-0.004	1.000		
	(0.001)	(0.655)	(0.614)	(0.029)	(0.790)	(0.702)	(0.195)	(0.669)	(0.011)	(0.593)	(0.737)	(0.000)	(0.283)	(0.124)	(0.597)	(0.648)			
HHI index	0.070	0.034	0.053	0.042	0.008	-0.010	0.081	0.163	-0.021	0.044	-0.012	-0.000	-0.272	-0.003	0.010	0.024	0.006	1.000	
	(0.000)	(0.001)	(0.000)	(0.000)	(0.406)	(0.303)	(0.000)	(0.000)	(0.030)	(0.000)	(0.212)	(0.987)	(0.000)	(0.771)	(0.299)	(0.015)	(0.569)		
ANAL	-0.095	-0.075	-0.223	0.706	-0.144	0.181	0.121	0.137	0.259	0.152	-0.192	0.010	0.086	0.211	0.005	0.386	-0.015	-0.055	1.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.315)	(0.000)	(0.000)	(0.648)	(0.000)	(0.128)	(0.000)	

Table OA1: Controlling for Additional Measures of Unpleasant Weather

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Visibility	-0.0104***	-0.0107***	-0.0103***	-0.00890*	-0.0129***	-0.0124***	-0.00867***	-0.00763***	-0.0164**
	(-5.09)	(-5.18)	(-5.05)	(-1.38)	(-6.12)	(-5.98)	(-4.25)	(-3.75)	(-2.07)
Temp.		0.000449							0.00725***
		(0.95)							(7.11)
Dew			-0.00112***						-0.00497***
			(-2.36)						(-4.39)
Sea-level Pressure				0.00161					0.00332
				(0.62)					(0.96)
Wind					0.0221***				0.00885***
					(9.16)				(2.65)
Max Wind						0.00494***			0.00359***
						(9.09)			(4.88)
Min Temp.							-0.00147***		-0.00117***
							(-6.23)		(-2.59)
Rain								0.226***	0.251***
								(7.52)	(5.67)
Constant	0.430***	0.407***	0.480***	-1.183	0.319***	0.297***	0.430***	0.344***	-3.283
	(10.75)	(8.78)	(10.72)	(-0.45)	(7.55)	(6.99)	(10.75)	(8.36)	(-0.94)
Baseline Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	11590	11590	11572	9900	11587	11584	11590	11590	9895
Adjusted R-sq	0.26	0.26	0.26	0.27	0.26	0.26	0.26	0.26	0.28

Notes: This table presents the regression results to test the effect of $Visibility$ on REM after controlling for various weather variables. See Appendices A and B for detailed variable definitions and descriptions. Numbers in parentheses represent t-statistics calculated based on standard errors clustered at the industry-year level. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Table OA2: Summary Statistics of Firm Characteristics (three months after fiscal year-end)

	N	Mean	Std. Dev.	Bottom 25%	Median	Top 25%
AEM (performance-adjusted)	3290	-0.020	0.118	-0.052	-0.011	0.025
AEM (modified Jones)	4501	-0.018	0.135	-0.046	-0.009	0.025
AEM Rank	4501	4.424	2.861	2.000	4.000	7.000
REM	4373	-0.053	0.400	-0.233	-0.039	0.129
REM Rank	4373	4.585	2.827	2.000	5.000	7.000
REM_{CFO}	4536	-0.009	0.154	-0.065	-0.013	0.036
Rank(REM_{CFO})	4536	4.490	2.896	2.000	5.000	7.000
REM_{PROD}	4474	-0.018	0.177	-0.099	-0.008	0.045
Rank(REM_{PROD})	4474	4.504	2.858	2.000	5.000	7.000
REM_{DISX}	4631	-0.027	0.242	-0.094	-0.000	0.067
Rank(REM_{DISX})	4631	4.652	2.758	2.000	5.000	7.000
Size	5472	7.159	1.933	5.848	7.046	8.301
BM	5464	1.492	31.147	0.211	0.397	0.692
ROA	5246	0.001	0.225	-0.014	0.044	0.093
Leverage	5512	0.507	0.215	0.351	0.515	0.661
Firm Age	7665	19.666	16.132	7.000	15.000	27.000
Big N	7649	0.837	0.369	1.000	1.000	1.000
Auditor Tenure	7649	3.850	2.960	1.000	3.000	5.000
Loss	5535	0.295	0.456	0.000	0.000	1.000
Sales	7776	5204.138	17051.645	177.285	671.110	2622.595
Sales Growth	6745	0.810	45.582	-0.016	0.073	0.197
Litigious	7788	0.214	0.410	0.000	0.000	0.000
INST%	7788	0.561	0.338	0.277	0.638	0.855
Credit Rating	1723	0.473	0.499	0.000	0.000	1.000
RET	6838	0.117	0.664	-0.179	0.063	0.301
StdSales	7042	633.403	2373.182	22.618	78.335	298.260
NOA	4985	-0.880	39.837	-0.506	0.039	0.332
HHI index	7788	0.280	0.189	0.165	0.215	0.344
ANAL	7699	8.797	7.467	3.000	6.000	13.000
PM 2.5 (Weighted Annual Mean)	7788	10.693	2.611	8.900	10.400	12.500

Notes: This table presents the descriptive statistics for the firm-level variables used in the analyses where Visibility is measured for three months after the fiscal year-end. See Appendix A for detailed variable definitions and measurement.

Table OA3: Summary Statistics of Weather-Related Characteristics (three months after fiscal year-end)

	N	Mean	Std. Dev.	Bottom 25%	Median	Top 25%
Temp.	7788	46.771	13.424	36.162	46.498	55.881
Dew	7034	34.452	13.202	23.527	33.427	43.805
Sea-level Pressure	6592	1017.884	2.728	1016.664	1018.186	1019.466
Visibility	6853	9.071	1.378	8.662	8.996	9.327
Wind	7644	6.322	2.014	5.008	6.283	7.596
Gust	6762	38.194	7.436	34.000	38.100	42.000
Max Wind	7527	26.084	6.117	22.000	26.000	29.900
Total Precip.	7761	3.498	11.567	0.030	0.091	0.146
Snow Depth	7788	0.220	0.875	0.000	0.000	0.000
Max Temp	7788	78.370	11.640	72.000	79.000	86.000
Min Temp.	7788	18.141	18.520	5.000	17.100	32.000
Fog	7788	0.089	0.113	0.011	0.066	0.121
Rain	7788	0.247	0.167	0.132	0.275	0.352
Snow	7788	0.109	0.164	0.000	0.011	0.187
Hail	7788	0.000	0.002	0.000	0.000	0.000
Thunder	7788	0.027	0.051	0.000	0.000	0.033
Tornado	7788	0.000	0.001	0.000	0.000	0.000

Notes: This table presents the descriptive statistics for the various weather variables used in the analyses where Visibility is measured for three months after the fiscal year-end. See Appendix B for detailed variable descriptions.

Table OA4: The Effect of Visibility on AEM (three months after fiscal year-end)

	(1) AEM (performance-adj.)	(2) AEM (modified Jones)	(3) AEM Rank
Visibility_AfterFY3	0.00239	0.00121	0.0396
	(1.55)	(0.93)	(0.75)
Fog	-0.000271	0.0114	0.633
	(-0.02)	(0.75)	(1.12)
Size	-0.00420*	-0.00295	-0.0963*
	(-2.06)	(-1.51)	(-2.20)
BM	0.00435	-0.000741	-0.0581
	(1.18)	(-0.42)	(-1.18)
ROA	0.289***	0.344***	3.495***
	(4.44)	(5.58)	(7.53)
Leverage	0.000290	-0.0177	-0.793**
	(0.02)	(-1.41)	(-2.73)
Firm Age	0.000267**	0.000282**	0.0155***
	(2.76)	(3.08)	(4.54)
Big N	-0.0265***	-0.0177*	-0.783***
	(-3.57)	(-2.06)	(-4.31)
Auditor Tenure	-0.000471	-0.000510	0.00278
	(-0.99)	(-1.10)	(0.18)
Loss	-0.0157	0.00288	-1.206***
	(-1.36)	(0.24)	(-7.06)
Sales Growth	0.00135	0.000778	-0.00260
	(0.33)	(0.95)	(-0.30)
Litigious	0.0290***	0.0241***	0.500*
	(4.10)	(3.34)	(2.25)
INST%	-0.00870	0.00112	-0.112
	(-1.42)	(0.20)	(-0.67)
RET	0.00466	0.000542	-0.0362
	(0.88)	(0.20)	(-0.48)
StdSales	0.000000114	0.00000152	0.0000529
	(0.06)	(0.89)	(0.82)
NOA	-0.000000308	0.0000578	0.00281**
	(-0.00)	(0.88)	(3.12)
REM	0.0801***	0.0836***	2.192***
	(10.85)	(10.18)	(13.24)
Constant	-0.000860	-0.00192	5.614***
	(-0.04)	(-0.12)	(9.60)
Year FE	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes
N	2226	2673	2673
Adjusted R-sq	0.32	0.33	0.21

Notes: This table presents the regression results to test the effect of *Visibility* on AEM when *Visibility* is measured for three months after the fiscal year-end. See Appendix A for detailed variable definitions. Numbers in parentheses represent t-statistics calculated based on standard errors clustered at the industry-year level. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Table OA5: Summary Statistics of Firm Characteristics (one year before actual end date)

	N	Mean	Std. Dev.	Bottom 25%	Median	Top 25%
AEM (performance-adjusted)	9204	-0.018	0.098	-0.051	-0.012	0.024
AEM	10717	-0.014	0.093	-0.045	-0.008	0.026
AEM Rank	10717	4.427	2.871	2.000	4.000	7.000
REM	10717	-0.071	0.424	-0.288	-0.053	0.142
REM Rank	10717	4.444	2.990	2.000	4.000	7.000
REM_{CFO}	10717	-0.008	0.115	-0.063	-0.012	0.039
Rank(REM_{CFO})	10717	4.544	2.863	2.000	5.000	7.000
REM_{PROD}	10717	-0.024	0.188	-0.117	-0.010	0.052
Rank(REM_{PROD})	10717	4.425	2.960	2.000	4.000	7.000
REM_{DISX}	10717	-0.039	0.242	-0.145	-0.011	0.076
Rank(REM_{DISX})	10717	4.410	3.002	2.000	4.000	7.000
Size	10717	6.906	1.672	5.749	6.835	7.990
BM	10717	0.582	0.707	0.250	0.434	0.719
ROA	10717	0.023	0.164	-0.004	0.047	0.093
Leverage	10717	0.471	0.214	0.305	0.473	0.626
Firm Age	10717	21.372	15.778	9.000	17.000	29.000
Big N	10717	0.838	0.368	1.000	1.000	1.000
Auditor Tenure	10717	4.718	3.379	2.000	4.000	7.000
Loss	10717	0.262	0.440	0.000	0.000	1.000
Sales	10717	2907.075	6828.545	235.106	749.957	2422.398
Sales Growth	10717	0.551	35.875	-0.012	0.077	0.191
Litigious	10717	0.391	0.488	0.000	0.000	1.000
INST%	10717	0.643	0.323	0.454	0.758	0.895
Credit Rating	10651	0.316	0.465	0.000	0.000	1.000
RET	10717	0.118	0.709	-0.213	0.038	0.317
StdSales	10717	292.812	737.753	23.330	75.129	238.917
NOA	10717	0.255	43.373	-0.084	0.144	0.374
HHI	10717	0.152	0.128	0.077	0.117	0.193
ANAL	10659	9.143	7.289	4.000	7.000	13.000
PM 2.5 (Weighted Annual Mean)	3383	10.487	2.703	8.800	10.300	12.200

Notes: This table presents the descriptive statistics for the firm-level variables used in the analyses where $Visibility$ is measured for one year before the actual fiscal year end date. See Appendix A for detailed variable definitions and measurement.

Table OA6: Summary Statistics of Weather-Related Characteristics (one year before actual end date)

	N	Mean	Std. Dev.	Bottom 25%	Median	Top 25%
Temp.	10717	58.053	8.102	52.640	58.021	62.303
Dew	10705	44.640	7.729	40.082	44.856	48.678
Sea-level Pressure	9133	1016.421	2.003	1015.866	1016.721	1017.469
Visibility	10717	9.265	1.580	8.837	9.141	9.510
Wind	10715	5.976	1.462	4.991	5.823	6.981
Gust	10563	44.554	8.558	39.000	44.100	49.900
Max Wind	10712	30.335	6.970	26.000	29.900	35.000
Total Precip.	10697	3.145	9.674	0.058	0.118	0.346
Snow Depth	10717	0.108	0.348	0.000	0.000	0.016
Max Temp	10717	97.594	9.418	95.000	98.100	102.000
Min Temp.	10717	12.623	16.488	1.000	12.000	28.000
Fog	10717	0.088	0.105	0.027	0.066	0.107
Rain	10717	0.290	0.134	0.194	0.314	0.375
Snow	10717	0.062	0.106	0.000	0.027	0.093
Hail	10717	0.001	0.002	0.000	0.000	0.000
Thunder	10717	0.068	0.062	0.003	0.060	0.115
Tornado	10717	0.000	0.001	0.000	0.000	0.000

Notes: This table presents the descriptive statistics for the various weather variables used in the analyses where Visibility is measured for one year before the actual fiscal year end date. See Appendix B for detailed variable descriptions.

Table OA7: The Effect of Visibility on Earnings Management (one year before actual end date)

	Accrual Earnings Management			Real Earnings Management	
	(1) AEM (performance-adj.)	(2) AEM (modified Jones)	(3) AEM Rank	(4) REM	(5) REM Rank
Visibility	0.000513	0.00155**	0.0317	-0.0103***	-0.0673***
	(0.93)	(2.71)	(1.81)	(-4.54)	(-4.23)
Fog	-0.00813	0.0106	0.132	0.133***	0.806**
	(-1.04)	(1.44)	(0.49)	(3.51)	(3.11)
Size	-0.00965***	-0.00516***	-0.219***	-0.0465***	-0.366***
	(-6.65)	(-4.57)	(-9.31)	(-10.01)	(-11.23)
BM	-0.00837***	-0.00414**	-0.182***	0.0298*	0.192*
	(-4.21)	(-3.05)	(-4.04)	(2.43)	(2.05)
ROA	0.352***	0.263***	3.750***	-0.774***	-4.754***
	(8.21)	(12.95)	(13.32)	(-15.01)	(-16.49)
Leverage	-0.0186**	-0.0210***	-0.515***	0.186***	1.546***
	(-3.09)	(-3.92)	(-3.60)	(8.94)	(10.60)
Firm Age	0.000261***	0.000263***	0.0160***	0.00155***	0.0121***
	(4.74)	(5.47)	(9.08)	(6.36)	(6.68)
Big N	-0.00297	-0.00710*	-0.232**	-0.0398***	-0.284***
	(-0.93)	(-2.46)	(-2.85)	(-3.44)	(-3.50)
Auditor Tenure	-0.000244	-0.000117	-0.00556	0.000909	0.00609
	(-1.09)	(-0.57)	(-0.75)	(0.84)	(0.80)
Loss	-0.00865	-0.0146***	-1.245***	-0.0726***	-0.358***
	(-1.05)	(-3.65)	(-14.63)	(-5.91)	(-4.45)
Sales Growth	-0.00967	-0.00000736	0.000995***	0.0000273*	0.0000880
	(-1.64)	(-0.28)	(3.54)	(2.30)	(1.18)
Litigious	0.0170***	0.000177	-0.380**	-0.325***	-1.882***
	(4.48)	(0.05)	(-3.25)	(-16.56)	(-14.68)
INST%	-0.0265***	-0.0223***	-0.607***	-0.0900***	-0.661***
	(-8.27)	(-7.97)	(-6.90)	(-6.75)	(-7.44)
RET	-0.000211	-0.00000108	-0.0218	-0.00885	-0.0204
	(-0.13)	(-0.00)	(-0.51)	(-1.51)	(-0.56)
StdSales	0.000000106	-0.00000129	-0.0000313	0.0000681***	0.000496***
	(0.06)	(-1.02)	(-0.74)	(4.67)	(4.45)
NOA	-0.000292	-0.0000121	0.000762		
	(-1.88)	(-0.37)	(1.92)		
REM	0.0539***	0.0570***	1.619***		
	(12.95)	(15.59)	(21.36)		
HHI				-0.0218	-0.292
				(-0.34)	(-0.61)
AEM				1.200***	7.531***
				(19.84)	(20.65)
Constant	0.0655***	0.0361***	6.769***	0.447***	8.005***
	(6.08)	(3.95)	(27.09)	(10.13)	(25.85)
Year FE	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes
N	9204	10717	10717	10717	10717
Adjusted R-sq	0.35	0.28	0.21	0.26	0.27

Notes: This table presents the regression results to test the effect of *Visibility* on AEM and REM when *Visibility* is measured for one year before the actual fiscal year end date. See Appendix A for detailed variable definitions. Numbers in parentheses represent t-statistics calculated based on standard errors clustered at the industry-year level. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Table OA8: Summary Statistics of Firm Characteristics (three months before actual period end date)

	N	Mean	Std. Dev.	Bottom 25%	Median	Top 25%
AEM (performance-adjusted)	8878	-0.018	0.098	-0.051	-0.012	0.024
AEM	10338	-0.014	0.093	-0.045	-0.008	0.026
AEM Rank	10338	4.418	2.871	2.000	4.000	7.000
REM	10338	-0.073	0.424	-0.290	-0.054	0.141
REM Rank	10338	4.433	2.994	2.000	4.000	7.000
REM_{CFO}	10338	-0.008	0.116	-0.063	-0.013	0.038
Rank(REM_{CFO})	10338	4.539	2.862	2.000	5.000	7.000
REM_{PROD}	10338	-0.024	0.188	-0.117	-0.011	0.051
Rank(REM_{PROD})	10338	4.415	2.961	2.000	4.000	7.000
REM_{DISX}	10338	-0.040	0.243	-0.146	-0.012	0.076
Rank(REM_{DISX})	10338	4.399	3.005	2.000	4.000	7.000
Size	10338	6.909	1.673	5.752	6.842	7.995
BM	10338	0.585	0.714	0.251	0.435	0.725
ROA	10338	0.022	0.164	-0.005	0.047	0.092
Leverage	10338	0.472	0.214	0.306	0.474	0.628
Firm Age	10338	21.396	15.808	9.000	17.000	29.000
Big N	10338	0.838	0.369	1.000	1.000	1.000
Auditor Tenure	10338	4.794	3.422	2.000	4.000	7.000
Loss	10338	0.263	0.440	0.000	0.000	1.000
Sales	10338	2921.056	6853.741	237.636	754.100	2443.352
Sales Growth	10338	0.564	36.526	-0.014	0.075	0.188
Litigious	10338	0.393	0.488	0.000	0.000	1.000
INST%	10338	0.645	0.322	0.461	0.760	0.896
Credit Rating	10274	0.318	0.466	0.000	0.000	1.000
RET	10338	0.118	0.717	-0.216	0.037	0.317
StdSales	10338	294.005	742.526	23.476	75.350	239.319
NOA	10338	0.264	44.153	-0.087	0.142	0.372
HHI index	10338	0.157	0.132	0.080	0.117	0.196
ANAL	10282	9.183	7.304	4.000	7.000	13.000
PM 2.5 (Weighted Annual Mean)	3270	10.431	2.699	8.800	10.100	12.200

Notes: This table presents the descriptive statistics for the firm-level variables used in the analyses where Visibility is measured for three months before the actual period year end date. See Appendix A for detailed variable definitions and measurement.

Table OA9: Summary Statistics of Weather-Related Characteristics (three months before actual period end date)

	N	Mean	Std. Dev.	Bottom 25%	Median	Top 25%
Temp.	10338	53.172	11.576	44.780	53.172	61.085
Dew	10331	40.564	10.779	33.507	40.033	46.863
Sea-level Pressure	8891	1017.720	2.343	1016.480	1018.065	1019.242
Visibility	10338	9.206	1.388	8.738	9.105	9.474
Wind	10337	5.834	1.620	4.664	5.815	6.941
Gust	10324	37.802	7.442	33.000	36.900	42.000
Max Wind	10336	25.977	5.522	22.000	26.000	28.900
Total Precip.	10335	3.192	10.150	0.051	0.103	0.168
Snow Depth	10338	0.102	0.497	0.000	0.000	0.000
Max Temp	10336	86.122	9.080	80.600	86.000	91.900
Min Temp.	10336	21.756	16.083	12.000	23.000	32.000
Fog	10338	0.095	0.098	0.033	0.066	0.132
Rain	10338	0.285	0.134	0.207	0.297	0.374
Snow	10338	0.064	0.104	0.000	0.011	0.088
Hail	10338	0.000	0.003	0.000	0.000	0.000
Thunder	10338	0.036	0.060	0.000	0.011	0.044
Tornado	10338	0.000	0.001	0.000	0.000	0.000

Notes: This table presents the descriptive statistics for the various weather variables used in the analyses where Visibility is measured for three months before the actual fiscal year end date. See Appendix B for detailed variable descriptions.

Table OA10: The Effect of Visibility on Earnings Management (three months before actual period end date)

	Accrual Earnings Management			Real Earnings Management	
	(1) AEM (performance-adj.)	(2) AEM (modified Jones)	(3) AEM Rank	(4) REM	(5) REM Rank
Visibility	0.000282	0.00137*	0.0264	-0.00941***	-0.0683***
	(0.46)	(2.11)	(1.34)	(-3.41)	(-3.51)
Fog	-0.00335	0.0155	0.388	0.182***	0.966***
	(-0.36)	(1.85)	(1.27)	(4.43)	(3.32)
Size	-0.00965***	-0.00545***	-0.221***	-0.0460***	-0.365***
	(-6.42)	(-4.67)	(-9.20)	(-9.69)	(-10.96)
BM	-0.00809***	-0.00425**	-0.186***	0.0305*	0.193*
	(-4.00)	(-3.09)	(-4.06)	(2.44)	(2.03)
ROA	0.348***	0.261***	3.702***	-0.762***	-4.673***
	(7.77)	(12.53)	(12.84)	(-14.40)	(-15.86)
Leverage	-0.0176**	-0.0207***	-0.530***	0.188***	1.559***
	(-2.81)	(-3.74)	(-3.63)	(8.87)	(10.49)
Firm Age	0.000277***	0.000269***	0.0158***	0.00160***	0.0123***
	(4.95)	(5.50)	(8.80)	(6.46)	(6.66)
Big N	-0.00333	-0.00763**	-0.256**	-0.0386**	-0.279***
	(-1.01)	(-2.58)	(-3.09)	(-3.26)	(-3.37)
Auditor Tenure	-0.000356	0.0000325	0.00196	0.000833	0.0104
	(-1.50)	(0.15)	(0.26)	(0.78)	(1.37)
Loss	-0.00926	-0.0151***	-1.234***	-0.0727***	-0.348***
	(-1.07)	(-3.68)	(-14.22)	(-5.81)	(-4.26)
Sales Growth	-0.00887	-0.00000635	0.00102***	0.0000280*	0.0000912
	(-1.51)	(-0.24)	(3.72)	(2.34)	(1.22)
Litigious	0.0179***	0.000583	-0.398***	-0.332***	-1.913***
	(4.58)	(0.16)	(-3.32)	(-16.51)	(-14.55)
INST%	-0.0259***	-0.0217***	-0.590***	-0.0930***	-0.671***
	(-7.81)	(-7.58)	(-6.58)	(-6.83)	(-7.38)
RET	-0.000273	-0.0000799	-0.0234	-0.00718	-0.00912
	(-0.17)	(-0.06)	(-0.55)	(-1.25)	(-0.25)
StdSales	0.000000159	-0.00000105	-0.0000213	0.0000672***	0.000493***
	(0.09)	(-0.82)	(-0.51)	(4.59)	(4.37)
NOA	-0.000303	-0.0000113	0.000799*		
	(-1.92)	(-0.35)	(2.07)		
REM	0.0538***	0.0569***	1.609***		
	(12.58)	(15.15)	(20.82)		
HHI index				-0.000348	-0.0516
				(-0.01)	(-0.11)
AEM				1.197***	7.466***
				(19.34)	(20.07)
Constant	0.0662***	0.0384***	6.798***	0.427***	7.915***
	(5.82)	(3.93)	(25.34)	(9.06)	(23.88)
Year FE	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes
N	8878	10338	10338	10338	10338
Adjusted R-sq	0.35	0.28	0.21	0.27	0.27

This table presents the regression results to test the effect of $Visibility$ on AEM and REM when $Visibility$ is measured for three months before the actual fiscal year end date. See Appendix A for detailed variable definitions. Numbers in parentheses represent t-statistics calculated based on standard errors clustered at the industry-year level. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.