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Clearing the smoke: How regional air pollution disciplines corporate ESG greenwashing

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Data Availability

The datasets generated by research during and/or analyzed during the current study are available in the Bloomberg and the CNRDS with restricted access.

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Clearing the smoke: How regional air pollution disciplines corporate ESG greenwashing?

Abstract

Drawing on legitimacy and stakeholder theories, this study examines how city-level air pollution is associated with corporate ESG greenwashing. Using a panel of 9,680 firm-year observations of Chinese A-share listed firms from 2013 to 2022, we find that firms located in cities with poorer air quality exhibit significantly lower levels of greenwashing, consistent with heightened environmental scrutiny and institutional pressure. This negative association is more pronounced among state-owned firms, which face heightened public responsibility and institutional accountability. The findings remain robust to alternative air pollution measures, two-way clustering, entropy balancing, and Heckman sample selection correction. Overall, this study provides additional evidence that local environmental conditions and ownership structures jointly influence corporate ESG disclosure behavior, highlighting the importance of environmental exposure and institutional accountability for ESG credibility in emerging markets such as China.

Keywords: Air pollution, ESG greenwashing, State-owned firms.

JEL Classification M14·Q53·Q58

1 Introduction

Air pollution represents one of the most critical global challenges of our time, prompting nations worldwide to deploy extensive regulatory and strategic efforts toward its mitigation (Zambrano-Monserrate & Soto, 2026). Unlike many environmental risks that are diffuse or temporally distant, air pollution is highly visible, politically sensitive, and closely regulated. Air pollution is closely linked to carbon emissions in particular, and it has recently become a top policy priority in many countries. Moreover, severe air pollution directly affects public health and social welfare, often attracting substantial media coverage, governmental intervention, and public scrutiny.[1]

A growing body of research suggests that ESG disclosure can enhance corporate legitimacy, reduce information asymmetry, and strengthen stakeholder confidence by signaling long-term strategic orientation (Seele & Gatti, 2017; Xiong et al., 2025). As ESG reporting becomes increasingly institutionalized, sustainability disclosure has evolved into an important component of firms' external communication and regulatory compliance strategies. However, growing concerns over ESG greenwashing suggest that such disclosures may not always reflect firms' actual environmental performance. ESG greenwashing generally refers to the selective exaggeration, omission, or distortion of sustainability-related information in order to project an image of environmental responsibility without corresponding substantive actions. Existing studies mainly explain greenwashing from the perspectives of corporate governance, managerial incentives, ownership structures, analyst coverage, media attention, and external monitoring (B. Deng et al., 2024; Y. Liu et al., 2023; Long et al., 2024; Tao et al., 2024; Yang et al., 2025), while relatively limited attention has been paid to the role of external environmental conditions especially air pollution. Prior studies suggest that heightened environmental pressure strengthens regulatory monitoring and increases the

[1] With the advancement of AI technology, individuals can easily monitor daily air quality levels via their smartphones.

reputational costs associated with environmental misconduct (Chen et al., 2023; J. Ren et al., 2024). Under such conditions, firms may face greater pressure to avoid exaggerated or symbolic ESG communication, thereby reducing incentives to engage in greenwashing. However, despite the pervasive macro-level impacts of environmental degradation, how individual corporations socially and behaviorally respond to regional air quality remains a remarkably under-researched domain in corporate sustainability literature.

The effect of environmental pressure may be particularly pronounced in emerging economies such as China, where government intervention plays a critical role in corporate decision-making and environmental governance. China provides a unique setting for this analysis because environmental regulation intensity and institutional enforcement vary substantially across regions.[2] In addition, state-owned enterprises (SOEs) are typically subject to stronger governmental oversight and political accountability, especially regarding environmental objectives and policy implementation (Chemmanur et al., 2024; Wei, 2021). Compared with non-SOEs, state-owned firms are therefore more likely to experience stronger regulatory and reputational pressure when environmental conditions deteriorate.

Against this backdrop, this study examines whether regional air pollution constrains corporate ESG greenwashing and whether this effect is more pronounced among state-owned enterprises. Using a panel of Chinese A-share listed firms from 2013 to 2022, we investigate the relationship between regional air pollution and ESG greenwashing and further examine whether the state ownership might affect this relationship. Empirical findings suggest that high air pollution area firms reduce firms' ESG greenwashing and this negative effect is more pronounced in SOE firms. Finally, robustness tests using entropy balancing, Heckman analysis confirm our main results.

[2] In China, air pollution levels vary significantly across regions depending on the degree of industrial development and the distribution of industries (Chen et al., 2022).

This paper has several contributions of these related literatures. First, this study extends the literature on the antecedents of corporate greenwashing by shifting focus from broad environmental pressures to the role of salient local environmental conditions. While prior research extensively documents that environmental regulations, public scrutiny, and regional pressures influence corporate environmental practices and disclosures (Bilicka et al., 2025; Deng et al., 2024; Du, 2015; Huang & Wei, 2023; K. Li et al., 2024; C. Liu et al., 2024; Yin et al., 2024), whether visible deterioration in the local environment such as poorer air pollution quality constrains greenwashing behavior remains underexplored. This study is significant in that it utilizes real-time air pollution data in China to empirically examine the direct impact of air pollution on corporate greenwashing.

Second, this study highlights the importance of institutional heterogeneity in shaping corporate ESG behavior. We show that the negative association between air pollution and greenwashing is more pronounced among SOEs, suggesting that state ownership amplifies the disciplining effect of environmental pressure through stronger regulatory oversight and political accountability. These findings contribute to the literature on environmental governance by demonstrating how institutional structures condition firms' responses to external environmental pressure. This study provides additional evidence that government involvement and institutional monitoring are important mechanisms constraining opportunistic ESG disclosure in emerging markets.

Third, while prior literature on the corporate and societal implications of air pollution has predominantly focused on Western jurisdictions, such as European economies (Dechezlepretre et al., 2020; Jiménez-Parra et al., 2018), this study provides a compelling departure by examining how macro-level environmental externalities shape micro-level corporate disclosure behaviors in China. Moving beyond the traditional view of air pollution as merely a physical or regulatory burden, our findings demonstrate that local environmental degradation functions as an external disciplining mechanism that constrains opportunistic ESG reporting and enhances disclosure credibility. Investigating this dynamic in China is particularly salient, as the nation

stands at the epicenter of aggressive environmental governance and rapid industrial transition within emerging markets. Consequently, this study extends the corporate sustainability literature by illuminating how regional environmental exposure and institutional scrutiny jointly regulate corporate ESG transparency in non-Western institutional settings.

2 Institutional setting in China and hypotheses development

2.1 Institutional setting in China

China provides an ideal institutional context for examining the link between air pollution and corporate greenwashing. Since the early 2010s, the Chinese government has implemented a series of policies to strengthen environmental protection, culminating in the 2015 revision of the EPL—often described as "the strictest environmental law in history" (Chemmanur et al., 2024; Yin et al., 2024). The EPL introduced continuous daily fines, executive accountability, mandatory information disclosure, and mechanisms for public participation. These measures significantly increased compliance costs for polluting firms and enhanced environmental transparency nationwide.

Moreover, the Chinese regulatory environment is characterized by a strong government presence in environmental governance. State-owned enterprises (SOEs) constitute a cornerstone of the national economy and are mandated to act as leading agents in the pursuit of China's sustainability agenda (Wei, 2021). SOEs face greater political and social pressure to align their operations with government environmental objectives, and their managers are often evaluated based on environmental performance metrics in addition to financial outcomes (Chen et al., 2022; D. Zhang, 2022). In contrast, non-SOEs may exhibit more flexible or opportunistic behavior, depending on the intensity of local enforcement and public scrutiny.

Another key feature of China's institutional environment is the government's extensive use of fiscal tools, such as environmental subsidies (Bai et al., 2019), green

credit (S. Zhang et al., 2021), and tax incentives (Zhu et al., 2023), to encourage sustainable business practices. However, these instruments also create room for opportunistic behavior if monitoring mechanisms are weak. Firms may exploit subsidies and green finance policies to portray themselves as environmentally responsible without substantive performance improvements, leading to policy-induced greenwashing. The coexistence of strong regulatory mandates and selective enforcement thus provides a unique setting for examining how environmental and institutional pressures jointly shape corporate ESG behavior.

Finally, China's comprehensive air quality monitoring system (https://air.cnemc.cn:18007/), which publishes city-level Air Quality Index (AQI) data in real time to the public, enables precise matching of environmental conditions with firm-level behavior.

2.2 Hypotheses development

2.2.1 Legitimacy and stakeholder perspectives on air pollution and ESG greenwashing

Legitimacy theory suggests that firms seek to align their activities and disclosures with prevailing social expectations in order to maintain legitimacy and secure continued access to external resources (Dowling & Pfeffer, 1975; Suchman, 1995). ESG disclosure therefore functions not only as an information mechanism but also as a strategic tool through which firms manage external perceptions and respond to stakeholder pressure. However, when ESG disclosure exceeds actual environmental performance, firms may engage in greenwashing by selectively exaggerating sustainability-related information.

Prior studies show that greenwashing is shaped by both internal incentives and external monitoring conditions (B. Deng et al., 2024; Long et al., 2024; Tao et al., 2024). Firms are more likely to engage in opportunistic ESG disclosure when external scrutiny is weak, and the probability of detection is low. Conversely, stronger public attention, regulatory monitoring, and media exposure increase the reputational and regulatory

costs associated with misleading sustainability communication, thereby constraining greenwashing behavior.

Air pollution represents a particularly prominent source of external environmental pressure operating at the regional macro-level. We propose that regional air quality influences firm-level ESG disclosure strategies through a multi-stage transmission mechanism. Specifically, severe city-level air pollution triggers heightened visual awareness among local stakeholders, prompting a surge in local media coverage, public concern, and governmental policy intervention (Deegan, 2002; S. Ren et al., 2024). This macro-level scrutiny quickly cascades down to the firm level, exposing corporations headquartered in heavily polluted cities to rigorous oversight from regulators, institutional investors, and environmental analysts. Under such intensified scrutiny, any discrepancy between a firm's public ESG claims and its actual environmental performance becomes significantly easier to detect, thereby dramatically increasing the firm's reputational risks, legal liabilities, and regulatory penalties. Admittedly, an alternative perspective rooted in symbolic legitimacy suggests that firms operating in highly polluted regions may face strong incentives to engage in *symbolic greenwashing*—using exaggerated ESG disclosures as a window-dressing tactic to project a responsible image, deflect external criticism, or evade immediate regulatory sanctions (Ashforth & Gibbs, 1990; Suchman, 1995). However, we argue that the viability of such symbolic management hinges on information asymmetry and low detection risk. In heavily polluted Chinese cities, real-time environmental monitoring systems and stringent policy enforcement (e.g., the Environmental Protection Law) drastically reduce information asymmetry. When local air quality deteriorates, regulators and the public become hyper-vigilant, making deceptive sustainability claims highly visible and costly. Consequently, the heightened risk of reputational backlash and regulatory penalties outweighs the short-term benefits of symbolic window-dressing. On balance, severe regional air pollution functions as an external disciplining mechanism that raises the expected costs of opportunistic communication. Firms operating in highly polluted cities are forced to align their ESG disclosures with

substantive environmental performance, thereby constraining their greenwashing behavior. Accordingly, we propose the following hypothesis one:

Hypothesis 1. *Regional air pollution is negatively associated with firm's ESG greenwashing.*

2.2.2 State ownership and the role of institutional pressure

Within the Chinese institutional context, state ownership constitutes a primary channel through which government objectives and regulatory priorities dictate corporate behavior (Bao & Liu, 2022; Luo & Tang, 2023). On the one hand, a competing line of argument suggests that state-owned enterprises (SOEs) possess strong political connections, which may grant them a "political shielding effect" that buffers them from regulatory enforcement and external monitoring. Under this view, SOEs might feel insulated enough to engage in symbolic ESG disclosures without fearing immediate sanctions.

On the other hand, we argue that in the realm of environmental governance, the political risks associated with greenwashing for SOEs far outweigh any potential shielding benefits. Unlike non-SOEs, SOEs function as political extensions of the state, and their top executives are Quasi-government officials whose career advancements are directly tied to political promotion tournaments and cadre evaluation systems (Chen et al., 2022; D. Zhang, 2022). Under China's target-responsibility system, local environmental performance and compliance are embedded into the Key Performance Indicators (KPIs) of SOE managers.

In regions experiencing severe air pollution, environmental issues become highly politically sensitive. Local governments and state-owned asset supervision commissions (SASAC) face intense pressure from central authorities to meet emission reduction targets. Under such heightened scrutiny, deceptive or exaggerated ESG reporting by an SOE is no longer viewed merely as a corporate disclosure flaw, but as

a political liability and a breach of public trust that directly jeopardizes executive promotion or invites administrative sanctions (H. Huang et al., 2025; Yin et al., 2024). Consequently, SOE executives face strong career-driven incentives to avoid opportunistic greenwashing and align their ESG disclosures with substantive environmental performance.

In contrast, non-SOEs operate with profit-maximizing objectives and are relatively detached from state cadre evaluation systems. While they face external market and media scrutiny, their lack of direct political accountability leaves greater room for opportunistic and symbolic ESG disclosures.

Accordingly, we propose the following hypothesis:

Hypothesis 2. *The negative association between regional air pollution and firm's ESG greenwashing is more pronounced for state-owned firms.*

3 Research methodology

3.1 Data and sample selection

This study selects A-share listed companies in the SHSE and SZSE from 2013 to 2022 as the research sample. First, we obtain information about the Air Quality Index (AQI) data from the China Research Data Services database (CNRDS) is obtained through the cleaning and processing of 24-hour real-time monitoring data provided by the Ministry of Ecology and Environment of the People's Republic of China (https://www.mee.gov.cn/). Second, we collect data on ESG disclosure from Bloomberg and ESG performance from CNRDS to construct a measure of greenwashing. Third, control variables and other financial data are collected from the China Stock Market & Accounting Research (CSMAR) databases. Finally, the variables are refined as follows: (1) firms in the financial industry are excluded, (2) firms under "ST" (Special Treatment, indicating financial distress) status are excluded, (3) observations with missing key variables are omitted. After winsorization, the final sample includes 9,680 firm-year observations.

3.2 Variable measurement

3.2.1 Measures of air pollution

To capture environmental conditions, this study employs multiple air pollution indicators. Specifically, we use the AQI, PM2.5, PM10, SO_2, NO_2, CO, and O_3 as alternative measures, since different pollutants may exert heterogeneous effects on firms' ESG performance. Considering the issues of missing pollution data in some cities and invalid matching between industrial firms and pollution information, we rely primarily on continuous data from 2013 to 2022 for 31 provinces and 201 major cities in China. For consistency, the natural logarithm of each of the seven indicators (*lnAQI*, *lnPM25*, *lnPM10*, *lnSO2*, *lnNO2*, *lnCO*, and *lnO3*) is used in our study.

3.2.2 Measures of greenwashing

Prior studies have adopted various approaches to measure corporate greenwashing, including symbolic–substantive discrepancies, media-based identification, selective disclosure, and ESG disclosure–performance gaps. Compared with alternative measures, the disclosure–performance gap approach offers advantages in terms of data availability, comparability, and empirical measurability, making it particularly suitable for large-sample panel analyses. Following recent ESG studies, we measure greenwashing as the discrepancy between ESG disclosure and ESG performance (Battisti et al., 2025; B. Deng et al., 2024; K. Li et al., 2024). This approach captures the extent to which firms overstate their ESG commitment relative to their actual ESG performance and has become widely used in the greenwashing literature.

Specifically, we follow Yu et al. (2020), Wang et al. (2024) and Deng et al. (2024) to construct the model (1).

$$Greenwash_{i,t} = \frac{ESG\,D_{i,t} - \overline{ESG\,D}}{\sigma_D} - \frac{ESG\,P_{i,t} - \overline{ESG\,P}}{\sigma_P} \quad (1)$$

We construct the ESG greenwashing measure based on the standardized discrepancy between a firm's ESG disclosure score and its actual ESG performance score. Because

the Bloomberg ESG disclosure rating and the CNRDS ESG performance evaluation utilize different measurement scales and scoring distributions, directly subtracting one from the other could introduce scale bias. To ensure comparability and empirical rigor, we first standardize both scores into Z-scores with a mean of zero and a standard deviation of one across the sample year.

We construct two dependent variables based on the formula. *Greenwash1* is defined as the difference between ESG disclosure and ESG performance, capturing the extent of greenwashing. *Greenwash2* is a dummy variable that equals one if *Greenwash1* is greater than zero, and 0 otherwise, indicating the presence of greenwashing behavior.

3.3 Empirical models

To examine the relationship between air pollution and greenwashing, we construct the following regression model (2). Specifically, we measure greenwashing in two ways: (1) the numerical gap separating ESG disclosure and ESG performance (*Greenwash1*), and (2) a binary variable indicating whether this gap is positive or not (*Greenwash2*). All control variables are provided in the <Appendix>.

$$Greenwash_{i,t} = \alpha_0 + \alpha_1 AirPollution_{i,t} + \alpha_2 Control_{i,t} + Indu_i + Year_i + \varepsilon_{i,t} \quad (2)$$

4 Empirical results

4.1 Descriptive statistics

< PLEASE INSERT TABLE 1 HERE>

Table 1 reports the sample selection process and the distributions of ESG greenwashing and air pollution (*lnAQI*) among Chinese A-share listed firms from 2013 to 2022. Panel A shows that the final sample comprises 9,680 firm-year observations after excluding observations with missing AQI, city, or ESG data. Panel B shows that 42.35% of firm-year observations are classified as greenwashing, with the proportion fluctuating over time rather than exhibiting a consistent upward trend. Panel C indicates that 85.30% of

observations have AQI levels below 100, while 14.70% are exposed to AQI levels above 100.

< PLEASE INSERT TABLE 2 HERE>

Table 2 presents the descriptive statistics of the main variables based on 9,680 firm-year observations. Greenwash1 shows substantial variation across firms, with a mean of -0.203 and a standard deviation of 1.274, while the mean of Greenwash2 indicates that approximately 42.35% of firm-year observations are classified as greenwashing. The air pollution variable (*lnAQI*) also exhibits considerable variation, with a mean of 4.198 and a standard deviation of 0.358. Overall, the results suggest substantial heterogeneity in firms' ESG behavior, financial characteristics, and environmental exposure.

< PLEASE INSERT TABLE 3 HERE>

Table 3 reports the correlation coefficients among the key variables. Air pollution indicators (AQI, PM2.5, PM10, SO_2, NO_2, and CO) are significantly and negatively correlated with ESG greenwashing measures. This suggests that firms located in regions with poorer air quality tend to exhibit lower levels of ESG greenwashing, providing preliminary support for Hypothesis 1.

4.2 Main results

< PLEASE INSERT TABLE 4 HERE>

Table 4 reports the baseline regression results examining the relationship between air pollution and ESG greenwashing. Panel A presents the results using the continuous greenwashing measure (*Greenwash1*), while Panel B reports the results using the binary measure (*Greenwash2*). In both panels, the coefficients of AQI, PM2.5, PM10, SO_2, and CO are consistently negative and statistically significant, indicating that firms located in more polluted regions tend to exhibit lower levels of ESG greenwashing. In contrast, NO_2 and O_3 do not exhibit statistically significant negative associations

with ESG greenwashing. This heterogeneity among pollutants can be attributed to differences in their physical visibility and public perceptibility. Particulate matter ($PM_{2.5}$ and PM_{10}) and primary smog-forming emissions (SO_2 and CO) generate highly visible visual cues, such as haze and reduced atmospheric clarity, which trigger immediate public awareness and intense stakeholder scrutiny. Conversely, invisible or less visually prominent gaseous pollutants like NO_2 and O_3 are less perceptible to the public without specialized monitoring equipment, thereby failing to generate the threshold level of public salience required to incentivize firms to curb symbolic ESG communications. Overall, the results provide consistent evidence of a negative association between air pollution and ESG greenwashing, lending support to Hypothesis 1. Therefore, in the context of China, it can be interpreted that firms located in regions with severe air pollution significantly reduce their ESG greenwashing, anticipating heightened scrutiny and prospective government inspections.

< PLEASE INSERT TABLE 5 HERE>

To further examine whether state ownership strengthens the negative association between air pollution and ESG greenwashing, we conduct subsample analyses comparing state-owned enterprises (*SOEs*) and non-state-owned enterprises (*non-SOEs*). SOEs are subject to greater government oversight and institutional accountability, making them more responsive to environmental pressures and regulatory expectations (Chemmanur et al., 2024; Jiménez-Parra et al., 2018). From the perspectives of legitimacy and stakeholder theories, SOEs may face stronger incentives to align their ESG disclosures with substantive environmental performance to maintain political legitimacy and stakeholder confidence.

Table 5 presents the subsample regression results using both continuous (*Greenwash1*) and binary (*Greenwash2*) measures of ESG greenwashing. For SOEs, the coefficients of air pollution (*lnAQI*) are significantly negative in both specifications ($\beta = -0.465$, $p < 0.01$; $\beta = -0.685$, $p < 0.01$, respectively). In contrast, the corresponding coefficients for non-SOEs are statistically insignificant. These findings suggest that the

negative association between air pollution and ESG greenwashing is more pronounced among SOEs, consistent with their greater exposure to institutional accountability and environmental scrutiny. Overall, the results provide evidence consistent with Hypothesis 2. Therefore, these empirical findings can be interpreted as indicating that state-owned enterprises (SOEs) face higher ESG hurdles in accordance with pro-environmental government policies, which consequently leads to a more pronounced, significant reduction in ESG greenwashing.

4.3 Alternative clustering specifications

An important feature of this study is the use of city-level air pollution data, which captures local environmental conditions more precisely than broader regional measures. However, firms located in the same city may be exposed to common environmental, economic, and regulatory conditions, potentially leading to correlated error terms. To address this concern, we re-estimate the baseline regressions using two-way clustered standard errors at the firm and city levels, accounting for both within-firm dependence and spatial correlation across firms within the same city.

< PLEASE INSERT TABLE 6 HERE>

Table 6 reports the results. The coefficients of AQI, PM2.5, PM10, SO_2, and CO remain negative and statistically significant, while those of NO_2 and O_3 are insignificant. These findings indicate that the negative association between air pollution and ESG greenwashing is robust to alternative clustering specifications. Overall, the results reinforce the evidence supporting Hypothesis 1 and highlight the importance of accounting for city-level dependence in firm-level ESG analyses.

4.4 Robustness tests

To ensure the robustness of our findings and address potential concerns regarding observable differences and sample selection, we conduct entropy balancing, ownership-

based entropy balancing, and Heckman two-stage selection analysis. Table 7 presents the results of these additional tests, which generally reinforce the baseline findings and ownership-related heterogeneity.

< PLEASE INSERT Table 7 HERE>

4.4.1 Entropy balancing analysis

To mitigate potential bias arising from observable differences in firm characteristics and ensure a balanced distribution of covariates between treatment and control groups, we employ entropy balancing. First, we transform *lnAQI* into a binary variable, where values above the sample median are coded as 1 and those below are coded as 0. Second, we set second-order moments for all covariates, including *Size*, *Lev*, *ROA*, *TAT*, *Growth*, *Age*, *Dual*, and *Inde*, to ensure balance in both means and variances across groups. Third, we impose third-order moment restrictions for continuous variables (*Size*, *Lev*, *ROA*, *TAT*, *Growth*, *Age*, and *Inde*) to further adjust for skewness and higher-order distributional differences.

After reweighting the samples through entropy balancing, we re-estimate the regression models. Columns (1) and (2) of Panel A in Table 7 present the results, showing that the coefficients of *lnAQI* remain significantly negative for both *Greenwash1* ($\beta = -0.112$, $p < 0.05$) and *Greenwash2* ($\beta = -0.170$, $p < 0.05$). These findings suggest that the negative association between air pollution and ESG greenwashing persists after balancing observable firm characteristics, providing further support for Hypothesis 1.

4.4.2 Heterogeneity

To further assess the robustness of the ownership-related heterogeneity documented in Table 5, we perform an additional entropy balancing exercise separately for SOEs and non-SOEs. This approach reduces observable covariate imbalances within each ownership group and allows us to examine whether the baseline patterns persist after reweighting.

Panel B of Table 7 reports the results. The coefficients of *lnAQI* remain

significantly negative for SOEs across both greenwashing measures ($\beta = -0.227$, $p < 0.01$; $\beta = -0.333$, $p < 0.01$), whereas the corresponding coefficients for non-SOEs are statistically insignificant. These findings are consistent with the baseline subsample results, suggesting that the negative association between air pollution and ESG greenwashing is concentrated among state-owned firms. Overall, the results provide additional evidence consistent with Hypothesis 2.

4.4.3 Heckman analysis

A potential concern is sample selection bias arising from the availability of ESG disclosure and performance data. Firms included in the final sample may differ systematically from excluded firms, potentially affecting the estimated relationship between air pollution and ESG greenwashing. To address this concern, we employ the Heckman two-stage selection approach.

In the first stage, we estimate a sample selection model in which Included equals one if a firm-year observation is retained in the final sample and zero otherwise. The estimated selection equation is used to construct the inverse Mills ratio (IMR), which is subsequently incorporated into the second-stage regressions to account for potential non-random sample selection. Panel C of Table 7 presents the results. The coefficients of *lnAQI* remain negative and statistically significant for both *Greenwash1* ($\beta = -0.229$, $p < 0.05$) and *Greenwash2* ($\beta = -0.071$, $p < 0.05$). The coefficients of IMR are also significantly positive, suggesting that sample selection is relevant to the outcome equations. Nevertheless, the negative association between air pollution and ESG greenwashing persists after incorporating the selection correction. These findings provide further evidence consistent with Hypothesis 1.

5 Conclusions and discussion

This study examines the association between regional air pollution and corporate ESG greenwashing within the Chinese institutional context. Using 9,680 firm-year observations from Chinese A-share listed firms over the period 2013 to 2022, we find

that firms located in cities experiencing higher levels of air pollution tend to exhibit significantly lower levels of ESG greenwashing. This negative association remains evident across multiple pollution indicators and alternative estimation procedures. Importantly, the association is more pronounced among state-owned enterprises (SOEs), these findings suggest that state ownership may play an important role in shaping corporate responses to environmental pressure.

More broadly, the findings are consistent with the view that air pollution may serve as an external source of governance pressure, rather than merely representing environmental deterioration. When environmental degradation becomes highly visible and politically salient, firms may face greater public scrutiny, reputational concerns, and regulatory attention, potentially discouraging symbolic or misleading ESG disclosure. In this sense, the study extends the discussion of greenwashing beyond traditional firm-level governance explanations and emphasizes the role of local environmental conditions in shaping corporate disclosure strategies.

The findings also carry important practical implications. As ESG reporting becomes increasingly important in global capital markets and regulatory systems, concerns regarding the credibility of sustainability disclosure continue to intensify. Our results suggest that policymakers should consider local environmental conditions when designing ESG disclosure oversight and monitoring mechanisms. Integrating city-level environmental information into ESG assessments may help identify firms operating under different levels of environmental pressure and facilitate more targeted scrutiny of disclosure practices. In addition, the stronger negative association among SOEs highlights the potential relevance of institutional accountability in shaping corporate responses to environmental challenges. Strengthening disclosure verification and coordinating environmental supervision with ESG reporting requirements may therefore help improve corporate transparency and reporting credibility.

Despite these implications, this study has several limitations. First, although we employ multiple pollution indicators and several robustness tests, unobserved regional characteristics may still jointly influence air pollution and corporate disclosure behavior.

Although we employ two-way clustering at both the firm and city levels alongside industry and year fixed effects to mitigate potential unobserved heterogeneity, a limitation of this study is that we could not fully control for time-varying city-level macroeconomic characteristics, such as city-level GDP per capita or regional industrial structure (e.g., the proportion of tertiary industries). Accordingly, the findings should be interpreted as associations rather than definitive causal effects. Second, air pollution is measured at the city level and may not fully capture firm-specific environmental exposure. Third, the analysis focuses on Chinese listed firms, and the findings may not be directly generalizable to countries with different ownership structures and regulatory environments. Future research could incorporate firm-level emissions data, examine multi-level institutional governance structures, and conduct cross-country comparisons to further explore how environmental pressure shapes corporate ESG disclosure behavior under different institutional settings.

Overall, this study provides evidence that local environmental conditions are negatively associated with corporate ESG greenwashing, particularly among state-owned enterprises. By linking city-level air pollution with firm-level ESG behavior, the study underscores the relevance of environmental exposure and institutional context to understanding the credibility of corporate sustainability disclosures.

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<Appendix> Variable Definition

Type	Variable	Symbol	Definition
Dependent variables	ESG Greenwashing	*Greenwash1*	The disparity between ESG disclosure (data from Bloomberg) and ESG performance (data from CNRDS)
		Greenwash2	According to the disparity between ESG disclosure and ESG performance, we create a dummy variable, value=1 if the Greenwash1 >0, otherwise 0
Independent variables	Air Quality Index	*lnAQI*	This is the logarithm of the yearly mean of the daily Air Quality Index which is a measure of harmful content in the air, including PM2.5, PM10, SO_2, NO_2, CO, and O_3, published by Chinese Ministry of Environmental Protection
	PM2.5	*lnPM25*	This is the logarithm of the average $PM_{2.5}$ index of the areas where the firm is located
	PM10	*lnPM10*	This is the logarithm of the average PM_{10} index of the areas where the firm is located
	SO_2	*lnSO2*	This is the logarithm of the average SO_2 index of the areas where the firm is located
	NO_2	*lnNO2*	This is the logarithm of the average NO_2 index of the areas where the firm is located
	CO	*lnCO*	This is the logarithm of the average CO index of the areas where the firm is located
	O_3	*lnO3*	This is the logarithm of the average O_3 index of the areas where the firm is located
Control variables	Company Size	*Size*	Ln (total company assets at end of period)
	Solvency	*Lev*	Solvency = total liability/total assets
	Return on Assets	*ROA*	Return on assets = net income/total assets
	Total Asset Turnover	*TAT*	Total asset turnover = sales revenue/average total assets
	Asset Growth	*Growth*	The annual growth rate of firms' total asset

	Company Age	*Age*	Natural logarithm of the number of years since the company was founded
	CEO Duality	*Dual*	Dummy variable, if the board of directors and CEO of the firm are concurrently held by the same person, the value is 1, otherwise the value is 0
	Board Independence	*Inde*	The ratio of the number of independent directors to the number of boards of directors
Other variables	Nature of Property Right	*SOE*	Property rights, value = 1 if the enterprise is state-owned enterprise, otherwise 0
	Industry fixed	*Indu*	Industry fixed effects
	Year fixed	*Year*	Year fixed effects

Table1 Summary statistics

Panel A. Sample selection process

Procedures	Observations
Chinese A-share listed companies in the SHSE and SZSE from 2013 to 2022	29,909
Less	
Missing AQI/city information	(3,174)
Firms without score of ESG disclosure and ESG performance	(17,055)
Final sample	9,680

Panel B. ESG greenwashing by Year

Year	*Greenwashing firm*		*Non- Greenwashing firm*		Total
2013	290	40.67%	423	59.33%	713
2014	291	40.87%	421	59.13%	712
2015	436	47.08%	490	52.92%	926
2016	360	40.96%	519	59.04%	879
2017	384	42.57%	518	57.43%	902
2018	418	42.74%	560	57.26%	978
2019	447	42.25%	611	57.75%	1,058
2020	459	41.96%	635	58.04%	1,094
2021	493	40.95%	711	59.05%	1,204
2022	521	42.92%	693	57.08%	1,214
Total	4,099	42.35%	5,581	57.65%	9,680

Panel C. Distribution of air quality index at different stages

Level	Freq.	Percent
AQI (0-50)	2,110	21.80%
AQI (50-100)	6,147	63.50%
AQI (100-150)	1,260	13.02%
AQI (150-200)	146	1.51%
AQI (200-300)	16	0.17%
AQI (300-500)	1	0.01%
Total	9,680	100.00%

This table presents the sample selection process, annual distribution of ESG greenwashing, and distribution of air quality levels among Chinese A-share listed firms from 2013 to 2022.

Table 2 Descriptive statistics

Variable	N. of Obs	Mean	S.D.	Min	P25	Median	P75	Max
Greenwash1	9,680	-0.203	1.274	-3.233	-1.016	-0.221	0.556	3.268
Greenwash2	9,680	0.423	0.494	0.000	0.000	0.000	1.000	1.000
lnAQI	9,680	4.198	0.358	3.469	3.922	4.174	4.437	5.109
lnPM25	9,680	3.684	0.446	2.755	3.362	3.644	3.985	4.805
lnPM10	9,680	4.204	0.407	3.423	3.893	4.195	4.492	5.244
lnSO2	9,680	2.338	0.751	0.843	1.808	2.187	2.791	4.463
lnNO2	9,680	3.508	0.337	2.491	3.277	3.541	3.759	4.244
lnCO	9,680	-0.181	0.314	-0.740	-0.408	-0.223	-0.008	0.796
lnO3	9,680	4.040	0.274	2.659	3.992	4.092	4.186	4.373
Size	9,680	23.240	1.330	20.470	22.300	23.130	24.030	27.070
Lev	9,680	0.475	0.197	0.077	0.323	0.485	0.626	0.894
ROA	9,680	0.045	0.060	-0.184	0.016	0.038	0.073	0.223
TAT	9,680	0.629	0.436	0.081	0.344	0.535	0.779	2.635
Growth	9,680	0.133	0.219	-0.256	0.011	0.086	0.196	1.211
Age	9,680	2.551	0.655	0.693	2.197	2.773	3.045	3.401
Dual	9,680	0.215	0.411	0.000	0.000	0.000	0.000	1.000
Inde	9,680	0.377	0.056	0.333	0.333	0.364	0.429	0.571
SOE	9,680	0.526	0.499	0.000	0.000	1.000	1.000	1.000

This table presents the yearly distributions of our full sample of 9,680 Chinese listing firm-year observations over the period 2013–2022. The complete descriptions of the variables are provided in Appendix.

Table3 Correlation analysis

	Greenw~1	*Greenw~2*	*lnAQI*	*lnPM25*	*lnPM10*	*lnSO2*	*lnNO2*	*lnCO*	*lnO3*	*Size*	*Lev*	*ROA*	*TAT*	*Growth*	*Age*	*Dual*	*Inde*
Greenwash2	0.777***																
lnAQI	-0.022**	-0.017*															
lnPM25	-0.018*	-0.014	0.979***														
lnPM10	-0.042***	-0.034***	0.966***	0.932***													
lnSO2	-0.055***	-0.043***	0.701***	0.702***	0.731***												
lnNO2	0.046***	0.029***	0.767***	0.788***	0.715***	0.556***											
lnCO	-0.028***	-0.024**	0.785***	0.798***	0.790***	0.800***	0.680***										
lnO3	0.015	0.015	-0.381***	-0.429***	-0.396***	-0.447***	-0.380***	-0.532***									
Size	0.259***	0.182***	-0.062***	-0.075***	-0.065***	-0.147***	-0.032***	-0.096***	0.090***								
Lev	0.092***	0.057***	0.041***	0.037***	0.043***	0.040***	0.032***	0.049***	-0.019*	0.500***							
ROA	0.017*	0.002	-0.011	0.000	-0.010	-0.009	0.037***	-0.023**	-0.007	-0.128***	-0.446***						
TAT	0.019*	0.009	-0.001	0.009	0.004	0.038***	-0.005	0.014	-0.028***	-0.005	0.090***	0.145***					
Growth	0.038***	0.035***	-0.015	0.000	-0.017*	-0.002	0.034***	0.011	-0.023**	-0.159***	-0.071***	0.327***	-0.028***				
Age	-0.010	-0.007	-0.076***	-0.090***	-0.064***	-0.047***	-0.105***	-0.088***	0.105***	0.226***	0.225***	-0.224***	0.011	-0.282***			
Dual	-0.024**	-0.021**	-0.076***	-0.074***	-0.080***	-0.067***	-0.046***	-0.060***	0.050***	-0.138***	-0.095***	0.095***	-0.012	0.140***	-0.211***		
Inde	0.052***	0.038***	-0.050***	-0.045***	-0.069***	-0.066***	-0.029***	-0.038***	0.017*	0.086***	0.024**	0.009	0.004	0.010	-0.013	0.083***	
SOE	0.085***	0.069***	0.135***	0.134***	0.121***	0.082***	0.088***	0.111***	-0.064***	0.296***	0.225***	-0.195***	0.009	-0.223***	0.369***	-0.326***	0.011

This table presents correlations for variables of interest which reports Pearson correlation coefficients between key variables for the pooled sample. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

Table 4 Baseline regression

Panel A. Continuous variable regression results

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
VARIABLES	*Greenwash1*	*Greenwash1*	*Greenwash1*	*Greenwash1*	*Greenwash1*	*Greenwash1*	*Greenwash1*
lnAQI	**-0.225****						
	(-2.30)						
lnPM2.5		**-0.157***					
		(-1.95)					
lnPM10			**-0.275*****				
			(-3.27)				
lnSO₂				**-0.176*****			
				(-3.32)			
lnNO₂					**0.168***		
					(1.76)		
lnCO						**-0.301*****	
						(-2.59)	
lnO₃							**0.154**
							(1.44)
Size	0.328***	0.327***	0.328***	0.319***	0.320***	0.326***	0.324***
	(12.29)	(12.25)	(12.36)	(12.05)	(11.96)	(12.30)	(12.19)
Lev	-0.265	-0.266	-0.250	-0.222	-0.274	-0.254	-0.272
	(-1.57)	(-1.57)	(-1.49)	(-1.32)	(-1.61)	(-1.51)	(-1.60)
ROA	-0.069	-0.065	-0.045	-0.010	-0.152	-0.091	-0.105
	(-0.18)	(-0.17)	(-0.12)	(-0.03)	(-0.39)	(-0.24)	(-0.28)
TAT	0.060	0.063	0.055	0.065	0.074	0.063	0.068
	(0.92)	(0.96)	(0.85)	(0.99)	(1.11)	(0.96)	(1.04)
Growth	0.396***	0.400***	0.388***	0.389***	0.410***	0.402***	0.411***
	(5.26)	(5.30)	(5.17)	(5.18)	(5.40)	(5.33)	(5.41)
Age	-0.083**	-0.084**	-0.081**	-0.073*	-0.085**	-0.083**	-0.087**
	(-2.03)	(-2.05)	(-1.99)	(-1.77)	(-2.08)	(-2.03)	(-2.11)

Dual	-0.046	-0.046	-0.050	-0.045	-0.040	-0.044	-0.043
	(-0.81)	(-0.80)	(-0.88)	(-0.80)	(-0.70)	(-0.77)	(-0.76)
Inde	0.579	0.594	0.530	0.567	0.648	0.608	0.629
	(1.30)	(1.33)	(1.19)	(1.26)	(1.44)	(1.36)	(1.41)
Constant	-6.373***	-6.734***	-6.118***	-6.632***	-7.893***	-7.320***	-7.871***
	(-8.67)	(-9.92)	(-8.69)	(-10.25)	(-11.75)	(-12.00)	(-10.72)
Observations	9,680	9,680	9,680	9,680	9,680	9,680	9,680
R-squared	0.094	0.093	0.096	0.096	0.093	0.094	0.092
Firm Cluster	YES	YES	YES	YES	YES	YES	YES
Indu FE	YES	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES	YES

Panel B. Binary variable regression results

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
VARIABLES	*Greenwash2*	*Greenwash2*	*Greenwash2*	*Greenwash2*	*Greenwash2*	*Greenwash2*	*Greenwash2*
lnAQI	**-0.305****						
	(-2.12)						
lnPM2.5		**-0.216***					
		(-1.85)					
lnPM10			**-0.388*****				
			(-3.16)				
lnSO₂				**-0.274*****			
				(-3.61)			
lnNO₂					**0.193**		
					(1.36)		
lnCO						**-0.494*****	
						(-2.96)	
lnO₃							**0.216**
							(1.39)
Size	0.408***	0.406***	0.409***	0.396***	0.397***	0.406***	0.402***

	(10.75)	(10.73)	(10.80)	(10.47)	(10.51)	(10.76)	(10.67)
Lev	-0.579**	-0.579**	-0.560**	-0.510*	-0.590**	-0.558**	-0.588**
	(-2.19)	(-2.19)	(-2.13)	(-1.93)	(-2.22)	(-2.11)	(-2.22)
ROA	-0.860	-0.854	-0.824	-0.756	-0.963	-0.882	-0.914
	(-1.40)	(-1.39)	(-1.34)	(-1.22)	(-1.55)	(-1.43)	(-1.47)
TAT	0.098	0.102	0.091	0.103	0.115	0.100	0.109
	(1.04)	(1.08)	(0.96)	(1.08)	(1.20)	(1.06)	(1.15)
Growth	0.620***	0.625***	0.609***	0.605***	0.637***	0.627***	0.639***
	(5.02)	(5.06)	(4.93)	(4.92)	(5.16)	(5.09)	(5.17)
Age	-0.097	-0.098	-0.094	-0.081	-0.100*	-0.097	-0.102*
	(-1.60)	(-1.61)	(-1.56)	(-1.33)	(-1.65)	(-1.59)	(-1.67)
Dual	-0.077	-0.076	-0.082	-0.076	-0.067	-0.074	-0.073
	(-0.89)	(-0.88)	(-0.95)	(-0.88)	(-0.79)	(-0.86)	(-0.85)
Inde	0.773	0.792	0.702	0.747	0.858	0.807	0.841
	(1.23)	(1.27)	(1.12)	(1.18)	(1.37)	(1.29)	(1.35)
Constant	-7.614***	-8.088***	-7.226***	-7.851***	-9.542***	-8.907***	-9.656***
	(-7.13)	(-8.23)	(-7.05)	(-8.37)	(-9.62)	(-10.09)	(-9.23)
Observations	9,680	9,680	9,680	9,680	9,680	9,680	9,680
Pseudo R-squared	0.040	0.040	0.042	0.042	0.040	0.041	0.040
Firm Cluster	YES	YES	YES	YES	YES	YES	YES
Indu FE	YES	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES	YES

This table reports the effects of air pollution on ESG greenwashing using alternative air pollution measures. Panel A presents OLS regression results for the continuous measure (*Greenwash1*), while Panel B reports logistic regression results for the binary measure (*Greenwash2*). All specifications include control variables and industry and year fixed effects, with standard errors clustered at the firm level. t-statistics are reported in parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Table 5 SOE vs. Non-SOE

	(1)	(2)	(3)	(4)
	SOE		Non-*SOE*	
VARIABLES	*Greenwash1*	*Greenwash2*	*Greenwash1*	*Greenwash2*
lnAQI	**-0.465*** **	**-0.685*** **	**-0.017**	**0.006**
	(-3.69)	**(-3.59)**	**(-0.12)**	**(0.03)**
Size	0.362***	0.486***	0.265***	0.289***
	(10.55)	(9.56)	(6.11)	(4.65)
Lev	-0.659***	-1.048***	0.209	0.004
	(-2.67)	(-2.81)	(0.95)	(0.01)
ROA	-0.939	-1.783*	0.691	-0.041
	(-1.44)	(-1.80)	(1.49)	(-0.05)
TAT	0.101	0.172	-0.014	-0.040
	(1.25)	(1.42)	(-0.13)	(-0.27)
Growth	0.438***	0.547**	0.359***	0.610***
	(3.15)	(2.53)	(4.07)	(4.02)
Age	-0.050	-0.023	-0.160***	-0.221***
	(-0.69)	(-0.22)	(-3.12)	(-2.81)
Dual	-0.068	-0.042	0.013	-0.011
	(-0.70)	(-0.29)	(0.19)	(-0.10)
Inde	0.410	0.652	0.724	0.695
	(0.65)	(0.79)	(1.21)	(0.71)
Constant	-6.289***	-8.138***	-5.825***	-6.061***
	(-6.20)	(-5.62)	(-5.10)	(-3.51)
Observations	5,094	5,094	4,586	4,585
Pseudo/R-squared	0.123	0.061	0.075	0.030
Firm Cluster	YES	YES	YES	YES
Indu FE	YES	YES	YES	YES
Year FE	YES	YES	YES	YES

This table reports subsample regression results by ownership type. Columns (1) – (2) present results for state-owned enterprises (*SOEs*), while Columns (3) – (4) report results for *non-SOEs*. All specifications include control variables and industry and year fixed effects, with standard errors clustered at the firm level. t-statistics are reported in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Table 6 Alternative clustering specifications

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
VARIABLES	*Greenwash1*	*Greenwash1*	*Greenwash1*	*Greenwash1*	*Greenwash1*	*Greenwash1*	*Greenwash1*
lnAQI	**-0.225****						
	(-2.26)						
lnPM25		**-0.157****					
		(-2.05)					
lnPM10			**-0.275****				
			(-2.42)				
lnSO2				**-0.176*****			
				(-3.52)			
lnNO2					**0.168**		
					(1.36)		
lnCO						**-0.301***	
						(-1.82)	
lnO3							**0.154**
							(0.75)
Control Variables Included	YES	YES	YES	YES	YES	YES	YES
Constant	-6.835***	-7.185***	-6.616***	-7.215***	-8.212***	-7.807***	-8.329***
	(-11.37)	(-12.84)	(-10.92)	(-11.63)	(-11.40)	(-13.39)	(-7.20)
Observations	9,680	9,680	9,680	9,680	9,680	9,680	9,680
R-squared	0.094	0.093	0.096	0.096	0.093	0.094	0.092
Firm Cluster	YES	YES	YES	YES	YES	YES	YES
City Cluster	YES	YES	YES	YES	YES	YES	YES
Indu FE	YES	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES	YES

This panel reports robustness tests using alternative air pollution measures. Standard errors are clustered at both the firm and city levels. Industry and year fixed effects are included in all specifications.

Table 7 Endogeneity analysis

Panel A. Entropy balancing

	(1)	(2)
VARIABLES	*Greenwash1*	*Greenwash2*
lnAQI	**-0.112****	**-0.170****
	(-2.14)	**(-2.12)**
Size	0.313***	0.388***
	(11.95)	(10.25)
Lev	-0.262	-0.549**
	(-1.58)	(-2.09)
ROA	-0.090	-0.860
	(-0.24)	(-1.41)
TAT	0.077	0.120
	(1.17)	(1.28)
Growth	0.409***	0.632***
	(5.38)	(4.99)
Age	-0.087**	-0.108*
	(-2.19)	(-1.80)
Dual	-0.043	-0.086
	(-0.76)	(-0.99)
Inde	0.521	0.723
	(1.17)	(1.15)
Constant	-6.976***	-8.404***
	(-11.52)	(-9.49)
Observations	9,680	9,680
Pseudo/R-squared	0.086	0.038
Firm Cluster	YES	YES
Indu FE	YES	YES
Year FE	YES	YES

Panel B. Entropy balancing for SOE vs. Non-SOE

	(1)	(2)	(3)	(4)
	SOE		Non-*SOE*	
VARIABLES	*Greenwash1*	*Greenwash2*	*Greenwash1*	*Greenwash2*
lnAQI	-0.227***	-0.333***	0.000	-0.021
	(-3.34)	(-3.03)	(0.00)	(-0.18)
Control Variables Included	Yes	Yes	Yes	Yes
Constant	-8.009***	-10.758***	-5.378***	-5.164***
	(-9.44)	(-8.72)	(-5.55)	(-3.59)
Observations	5,094	5,094	4,586	4,585
Pseudo/R-squared	0.115	0.058	0.067	0.027
Firm Cluster	YES	YES	YES	YES
Indu FE	YES	YES	YES	YES

Year FE	YES	YES	YES	YES

Panel C. Heckman analysis

	(1)	(2)	(3)
VARIABLES	*Included*	*Greenwash1*	*Greenwash2*
lnAQI		-0.229**	-0.071**
		(-2.32)	(-2.15)
Size	0.919***	0.542***	0.149***
	(24.77)	(7.84)	(7.68)
Lev	-1.322***	-0.608***	-0.193***
	(-8.21)	(-3.09)	(-3.14)
ROA	0.601***	0.015***	0.000
	(3.77)	(4.39)	(0.34)
TAT	0.022	0.056	0.014
	(0.43)	(0.98)	(0.82)
Growth	0.133***	0.220***	0.082***
	(3.84)	(5.40)	(6.14)
Age	0.296***	-0.004	0.003
	(8.42)	(-0.08)	(0.19)
Dual	0.073*	-0.027	-0.013
	(1.65)	(-0.45)	(-0.65)
Inde	0.085	0.414	0.139
	(0.23)	(0.98)	(1.01)
IMR		0.546***	0.147***
		(3.92)	(3.51)
Constant	-20.145***	-12.106***	-2.816***
	(-25.22)	(-7.08)	(-5.75)
Observations	26,731	9,680	9,680
R-squared	0.362	0.098	0.057
Firm Cluster	YES	YES	YES
Indu FE	YES	YES	YES
Year FE	YES	YES	YES

This table reports endogeneity analyses using entropy balancing and the Heckman two-stage approach. Panels A and B present entropy-balanced regression results for the full sample and ownership-based subsamples, respectively. Panel C reports the Heckman selection model, where Included indicates sample inclusion and IMR denotes the inverse Mills ratio. All specifications include control variables and industry and year fixed effects, with standard errors clustered at the firm level. t-statistics are reported in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Supplementary Files

This is a list of supplementary files associated with this preprint. Click to download.

- DATA.zip