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Adjusted air pollution exposure and corporate innovation investment: Evidence from China

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Abstract

Using a novel measure of air pollution exposure adjusted for the heterogeneity of exposures and the extent of local air pollution, we find a significant negative relationship between adjusted air pollution exposure and corporate innovation investment. This finding still holds after controlling for endogeneity and conducting a series of robustness tests. While the relationship is mediated through net operating cash flows and debt financing costs, we also find that firms with high adjusted air pollution exposure might have deteriorated productivity of R&D personnel, which ultimately hinders innovation input and output. However, state ownership appears to mitigate this adverse effect of adjusted air pollution exposure. Furthermore, the adverse effects of air pollution exposure on innovation investment are more pronounced among firms that disclose environmental information, exhibit low managerial risk tolerance, operate in non-polluting industries, or are located in developed and less polluted regions. Additionally, the negative impact is particularly evident in the subsample of firms after the signing of the 2015 Paris Agreement. This study sheds light on the importance of adjusted air pollution exposure and its influence on corporate investment in China.

KEYWORDS
adjusted air pollution exposure, corporate innovation investment, debt financing cost, net operating cash flow

JEL CLASSIFICATION
G38, O31, Q53, Q56

1 | INTRODUCTION

Air pollution is known to harm human physical and mental health,[1] and financial economists recognize that financial market performance is not immune to poor air quality. A strand of the literature suggests that air pollution affects the resources and performance of individual firms, such as worsened cost of debt financing (Tan et al., 2022), decreased stock returns (Levy & Yagil, 2011), and decreased availability of bank loans (Tan et al., 2021). Furthermore, some papers find the influence of air pollution on decision-making for firms' policies and activities, such as decreased corporate innovation (Tan & Yan, 2021), reduced the firm's investment efficiency (He & Lin, 2022), and the adoption of more conservative accounting policies (Wu et al., 2022), among others.

Previous studies have primarily relied on country- or city-level air quality index (*AQI*) to examine the impact of air pollution on individual firms' behaviors and activities. Applying the AQI implicitly assumes that all firms in the same regions have the same exposure to air pollution shocks. However, although air pollution does not differ in a region, the exposure of firms to air pollution does. Despite this variation, there is a lack of research systematically measuring how different degrees of air pollution exposure affect specific firm's decision-making and investment activities. This paper addresses this gap by developing a novel metric—adjusted air pollution exposure, which combines city-level AQI with the firm-level exposure to air pollution. This measure captures both the firms' exposures to abnormal air pollution and the firms' headquarters' air pollution levels, confirming heterogeneity among firms' exposures to air pollution.

To construct our main independent variable—adjusted air pollution exposure (*A_AQI exposure*), we consider both local air pollution and firm-specific sensitivity to abnormal air pollution. The first is the local air pollution. The important dimension is that air pollution is an economic "bad" and is considered a negative externality. In other words, a zero or a very low AQI is always desirable. Second, each firm in different industry and location would have different exposure to the local air pollution. Following Bali et al. (2017) and Brogaard and Detzel (2015), we adopt the Fama–French three-factor model to estimate firm-level AQI sensitivity by regressing each firm's excess return on the market, size, value, and the air pollution anomaly risk.[2] This approach enables us to measure a firm's sensitivity to variations in abnormal air pollution levels, and assumes that the possible effects of anomalous variations in air pollution on the firm value would be reflected, at least in part, in stock prices. Because firms may be more susceptible to significant increases or decreases in air pollution, we utilize the absolute value of the anomaly variable coefficient (*AQI sensitivity*) to quantify firm-level air pollution exposure (*AQI exposure*) (Nagar et al., 2019). However, this approach to air pollution exposure alone overlooks the intrinsic negative externalities associated with air pollution. More specifically, we find that firms in China's less-polluted southern provinces are generally more sensitive to abnormal air pollution than those in the high-polluted northern provinces.[3] This means that firms located in high air pollution areas do not necessarily incur high air pollution exposures, suggesting that neither pollution levels nor firm sensitivity alone fully capture the true exposure. To address this, we develop adjusted air pollution exposure by multiplying firm-level AQI exposure with city-level AQI,[4] offering a more comprehensive measure of how air pollution affects corporate behaviors.

We focus on corporate innovation investment because it is crucial to a firm's competitiveness and growth (Porter, 1985), and it has the ability to drive sustained growth, competitive advantage, risk mitigation, and diversification in a rapidly changing business environment. Scholars study the factors affecting innovation from various perspectives, including external and internal factors. External factors that can increase corporate innovation include government subsidies (Zhang & Guan, 2018), political connections (Su et al., 2019), and higher-educated immigrants (Fassio et al., 2019). Internal factors that can increase corporate innovation include cash holdings and profitability (Almeida et al., 2004), executive team cognition (Wang et al., 2019), foreign management experience (Yuan & Wen, 2018), mutual funds' holdings (Chi et al., 2019) and exports (Chen et al., 2018); conversely, financing constraints (Silva & Carreira, 2012) have been found to hinder corporate innovation. However, little attention has been given to how heterogeneous air pollution exposure affects corporate innovation investment—a gap this study aims to fill.

Our study is related to two theories. Strategic growth option theory suggests that firms may respond to uncertainty by investing in innovation activities to secure their market share and sustain competitive advantage (Kulatilaka & Perotti, 1998; Tajaddini & Gholipour, 2021). As a form of uncertainty, high adjusted air pollution exposure may prompt firms to accelerate innovation investment to seize opportunities, increase market shares, and achieve sustainable development. However, real options theory argues that uncertainty increases the value of the option to wait, and firms can avoid sunk costs by deferring risky investment projects. Empirical evidence shows that rising uncertainty tends to reduce firms' investment (Kelly et al., 2016; Pastor & Veronesi, 2012). In addition, some studies find that uncertainty increases financing costs and reduces future cash flow, thereby exacerbating financing constraints and decreasing corporate innovation investment (Lee & Wang, 2021; Xu, 2020).

To contribute to the ongoing debate, our paper investigates the effect of adjusted air pollution exposure on innovation investment among Chinese listed firms. Furthermore, we also analyze its impact on patent applications as a robustness check. China provides a suitable setting for this analysis for three main reasons. First, air pollution is one of the most challenging environmental problems facing developing countries such as China and India (WHO, 2021). Since 2012, the Chinese government has prioritized environmental governance and sustainable development through structural reforms and regulatory policies (CBRC, 2014B).[5] Second, China has a notable disparity in pollution levels across cities (Dong et al., 2021). This will also result in high variations in both air pollution and adjusted air pollution exposures. Third, China has experienced rapid economic development since the 1980s. It has strongly emphasized corporate innovation throughout the process, and its innovation activities and research and development investment are comparable to many developed markets (Hao et al., 2020). Thus, using the Chinese stock market as a platform to study the impact of adjusted air pollution exposure on corporate innovation investment would be meaningful.

Our paper examines the impact of adjusted air pollution exposure of the firm on its innovation investment using a sample that includes 16,952 firm-year observations of 3197 listed firms in mainland China from 2010 to 2022. We find that the adjusted air pollution exposure is negatively related to corporate innovation investment. The results are economically meaningful: a one standard deviation increase in adjusted air pollution exposure is associated with a 1.94% decline in corporate innovation investment. The findings remain robust after a series of robustness checks and endogeneity tests, including controls for multiple fixed effects and macroeconomic uncertainty, the use of propensity score matching (PSM) and a staggered difference-in-difference (DID) approaches. Mediation analysis reveals that reduced net operating cash flows and increased financing costs are key channels through which adjusted air pollution exposure inhibits corporate innovation investment. We also find that firms with high adjusted air pollution exposure could face challenges such as increased absenteeism and reduced efficiency among R&D personnel, which ultimately hinders innovation input and output.

Additional analysis shows that firms with higher adjusted air pollution exposure tend to shift their focus from general technological innovation toward green innovation to address regulatory or reputational risks. Moreover, we find that firm-specific factors, such as environmental information disclosure, manager's risk tolerance, industry types (polluters or non-polluters); and external factors, such as the level of regional development and pollution levels, shape the relationship between adjusted air pollution exposure and innovation investment. Notably, the negative impact intensifies following the 2015 Paris Agreement.

Our paper differs from some similar existing studies in the following ways.[6] For example, Liu et al. (2024) utilize country-level annual $PM_{2.5}$ and CO_2 emissions as measures of air pollution and identify its negative impact on corporate R&D in emerging markets. In contrast, we develop a firm-level adjusted air pollution exposure metric by combining city-level AQI which captures six major pollutants[7] with firm-specific exposure to air pollution estimated using Fama–French three factor model, thereby providing a more holistic measure. Sautner et al. (2023) develop a firm-level climate change exposure based on earning call transcripts, covering data from over 10,000 firms across 34 countries between 2002 and 2020. Their findings reveal that firms with higher climate change exposure are more likely to create green jobs and file green patents but also face heightened financial risks. Our study shares a common focus with Sautner et al. (2023) in emphasizing the importance of granular, firm-level data to better understand the impact of environmental factors—whether climate change or air pollution—on businesses. However, the key distinction lies in the scope and nature of the exposures studied. First, climate change exposure reflects long-term, systemic risks, whereas air pollution exposure is more immediate and localized, affecting health, productivity, and operational dynamics. Moreover, their firm-level exposure is constructed using earning calls data, which tends to be more subjective.[8] In comparison, we use the Fama–French three-factors model to capture firms' exposures to abnormal air pollution (*AQI exposure*) and construct a more objective metric—adjusted air pollution exposure—by multiplying firm-level AQI exposure with the local AQI index. This adjusted measure provides a comprehensive and objective perspective on the impact of air pollution on firm behavior.

We make the following contributions to the literature. First, we propose a novel firm-level measure of adjusted air pollution exposure by combining city-level AQI with firm-specific exposure estimated using trading data and the Fama–French three-factor model. This measure captures both the intensity of local pollution and firms' sensitivity to it, offering a more comprehensive view of environmental uncertainty. Second, our paper provides evidence that adjusted air pollution exposure negatively affects corporate innovation investment. To our knowledge, this is among the first studies to investigate the effect of firm-specific air pollution exposure on innovation investment. Third, we identify channels through which firms with higher adjusted air pollution exposure reduce innovation investment, primarily by decreasing corporate net operating cash flows and increased financing costs, supporting the real options theory. Furthermore, we also provide the evidence that firms with high adjusted air pollution exposure may shift their focus toward environmentally adaptive technologies (green innovation) to manage regulatory or reputational risks.

The paper is structured as follows: in Section 2, we review the theoretical background and propose the hypotheses. In Section 3, we describe the data and methodology. In Section 4, we present and discuss our empirical results, and in Section 5, we conclude the paper.

2 | LITERATURE REVIEW AND HYPOTHESIS DEVELOPMENT

2.1 | The impact of air pollution

Environmental issues have become the focus of the government and scholars due to the global warming caused by economic development and the aggravation of pollution emissions. Air pollution is one of the heaviest types of environmental pollution worldwide, killing an estimated seven million people worldwide every year (WHO, 2022). The early studies pay more attention to the air pollution and individuals, such as the individual health and sentiments/moods (Bakian et al., 2015; Graff Zivin & Neidell, 2013). An increasing number of papers have begun to link air pollution to a wide range of macroeconomic activities (Chay & Greenstone, 2005; Ebenstein et al., 2015). Recently, financial economists have extended this line of research to examine the impacts of air pollution on firms' accounting and other financial policies, investment policies, and activities.

Several studies focus on the effects of air pollution on the firm's accounting policies, financial report quality, and internal control quality. For example, Wu et al. (2022) find that increased air pollution induces firms to follow more conservative accounting practices and utilize more conservative estimates in their reporting. Jiang et al. (2022) find that higher air pollution promotes earnings management by lowering labour productivity and strengthening executives' negative sentiments. Further analysis finds that air pollution transfers firms' real earnings management to accrual earnings management. Hu et al. (2022) find that firms' internal control quality and financial reporting quality are significantly and negatively associated with the severity of air pollution in their home cities because the mood of managers becomes more negative as levels of air pollution increase and results in a management that is less motivated, less effective, with lower decision quality, which leads to worse internal control quality and financial reporting quality.

Research exploring the influence of air pollution on firms' decision-making has gained momentum in recent years. Zhang et al. (2021) find that initial public offerings (IPOs) are under-priced for firms located in areas with severe air pollution compared to those with less air pollution. Liu et al. (2021) show that firms respond to increased air pollution by using more capital and less labor to remain competitive. Tan et al. (2021) find that air pollution drives a pessimistic mood and/or weakens the cognitive ability of management, leading to poor operations and an increase in precautionary needs for more cash due to pollution abatement or decreased availability of bank loans. He and Lin (2022) also find a similar adverse impact on managers' moods that reduces firms' investment efficiency.

In addition, a few papers examine the impacts of air pollution on corporate innovation. Tan and Yan (2021) find that air pollution reduces corporate innovation, as measured by patents, because it drains financial resources, constrains firms even more, and increases environmental governance costs. Tan and Yan (2021) and Wang et al. (2021) find that air pollution adversely affects the psychology of executives, negatively affecting their decision-making regarding innovation, which ultimately reduces corporate innovation.

Existing research mainly relies on city-level air quality indicators to investigate how air pollution influences firms' activities and behaviors. When applying the AQI, it is implicitly assumed that all firms in the same areas are equally exposed to air pollution shocks. Although air pollution does not differ by location, businesses' susceptibility to it does. This is one of the limitations of the current literature on air pollution.

2.2 | Corporate innovation

Innovation is a key component of economic expansion. Technology accumulation stimulates long-term economic development, supported by innovation (Change, 1990). According to Fritsch (2017), firms are the primary forces behind innovation. Through innovation, they gain a competitive advantage and momentary monopolistic power, which generates abnormal profit.

Many other papers study the factors affecting corporate innovation from various perspectives, including external and internal factors. By investigating the influence of external factors on corporate innovation, Zhang and Guan (2018) find that direct government subsidies benefit corporate innovation in the short term but hinder long-term innovation performance. Tsai et al. (2019) show that political connections have positive effects on corporate innovation. Fassio et al. (2019) find that higher-educated immigrants have a positive effect on innovation. By examining the impact of internal factors on corporate innovation, Almeida et al. (2004) discover that cash holdings and profitability are positively correlated with innovation. Silva and Carreira (2012) find that financing constraints can significantly inhibit corporate innovation. In addition, Yuan and Wen (2018) find that foreign management experience has a positive impact on corporate innovation. Chi et al. (2019) show that mutual funds' holdings significantly increase corporate innovation, but gray institutional holdings (such as insurance companies and pension funds) and qualified foreign institutional investors' holdings have little or no significant impact on innovation.

The existing literature on the factors influencing corporate innovation has predominantly focused on the entity level, such as enterprises, governments, and markets. While some studies have examined the role of natural environmental factors, including city-level AQI, city-level $PM_{2.5}$ levels, or climate change exposure (Liu et al., 2024; Sautner et al., 2023). These measurements often lack comprehensiveness or objectivity. Therefore, a deeper understanding of how adjusted air pollution exposure impacts corporate innovation investment is necessary.

In addition, innovation investment stands out for its potential to drive sustained growth, competitive advantage, risk mitigation, and diversification in a rapidly changing business environment. Patent applications are considered the output of innovation. Fang et al. (2014) suggest that compared with R&D investment—which measures observable innovation input—patenting activity is a good proxy for corporate innovation because it captures both innovation output and the efficiency of corporate innovation. Thus, our paper also investigates the effects of the adjusted air pollution exposure on the output of innovation as a robustness test.

2.3 | Hypothesis development

Our study is motivated by two opposing theories on the relationship between uncertainty and innovation investment.

According to strategic growth option theory, uncertainty might encourage investment in a growth option under imperfect competition. The reasoning behind this theory is that uncertainty can generate a growth option. While delaying investments could leave the investment opportunity to other competitors, taking immediate action could deter new entrants and strengthen market share and profitability (Kulatilaka & Perotti, 1998), thus increasing competitive advantage in the future. Similarly, Weeds (2002) shows that waiting loses value when firms face competition or when investments can lead to worthwhile expansion prospects. Moreover, Van Vo and Le (2017) find that firms that face higher uncertainty measured by idiosyncratic return volatility invest more in R&D, and the effect is more pronounced for firms in more competitive industries. Atanassov et al. (2015) document that R&D investment dramatically increases in gubernatorial election years.

In conclusion, we have reason to suspect that firms with high adjusted air pollution exposure may increase their investment in innovation to capture market share and realize sustainable development. Accordingly, we propose the following hypothesis:

Hypothesis 1a. (H1a): *Adjusted air pollution exposure positively impacts corporate innovation investment*.

In contrast to strategic growth option theory, the real option theory suggests that if an investment is irreversible, the investment opportunity can be regarded as an option held by the enterprise, and the uncertainty increases the value of the option to wait (Cui et al., 2021; Narayan et al., 2021). Therefore, enterprises tend to reduce or postpone investments in response to high uncertainty risks. From the risk aversion perspective, the enterprise would reduce operational risk by reducing investment in a business environment with vague and poor expectations in the presence of high-uncertainty (Bloom, 2007). Moreover, Bloom et al. (2018) show that the "wait-and-see" attitude causes the delay of investment when the economy suffers from uncertainty shocks. In short, by deferring investment and keeping the option alive, firms can avoid costly mistakes and wait for additional information about an uncertain future.

Unlike traditional investments, innovation plays an important role in a firm's competitiveness, but requires a longer time horizon and carries higher tail risk. The option to wait is particularly significant for investments in research and development (R&D), given that innovation involves exploring unknown approaches and untested methods (Ferreira et al., 2014), requiring substantial investment in intangible assets. Previous studies find that various types of uncertainties reduce R&D investment. For example, Goel and Ram (2001) show that inflation uncertainty has a stronger negative impact on R&D investment than non-R&D investments in nine OECD countries. Using German data, Czarnitzki and Toole (2011) find that market uncertainty reduces R&D investment. Similarly, Bhattacharya et al. (2017), using data from 43 countries, find that policy uncertainty measured by national elections adversely affects a country's innovation. Additionally, several studies suggest that uncertainty increases financing costs and reduces future cash flow, thereby exacerbating financing constraints and decreasing corporate innovation investment (Lee & Wang, 2021; Xu, 2020).

Based on the above analysis, we contend that firms with high adjusted air pollution exposure will suffer more from the adverse effects of this uncertainty. Therefore, managers may choose to reduce or postpone firms' innovation investment. We propose that firms with high adjusted air pollution exposure would exacerbate their operational risk and financial distress and be more likely to take a "wait-it-out" decision and we provide the following hypothesis:

Hypothesis 1b. (H1b): *Adjusted air pollution exposure negatively impact corporate innovation investment*.

3 | DATA AND METHODOLOGY

3.1 | Sample selection and data sources

We study all Chinese A-share firms listed on the Shanghai and Shenzhen stock exchanges from 2010 to 2022. Following Cui et al. (2021), we exclude firm-year observations with missing R&D expenditure data. Additionally, we remove (1) financial services firms, (2) special treatment (ST) firms, and (3) firm-year observations without sufficient financial data to construct control variables for regression analysis. Data on R&D investment, patents, Fama–French factors, stock returns, and accounting information are all obtained from the China Stock Market and Accounting Research (CSMAR). The final sample includes 16,952 firm-year observations of 3197 unique firms in mainland China from 2010 to 2022.

3.2 | Variable construction

3.2.1 | Air pollution data

The AQI is the most widely used indicator of air pollution.[9] It is constructed based on the levels of six atmospheric pollutants: sulfur dioxide (SO_2), nitrogen dioxide (NO_2), suspended particulates smaller than 10 μm in aero- dynamic diameter (PM_{10}), suspended particulates smaller than 2.5 μm in aerodynamic diameter ($PM_{2.5}$), carbon monoxide (CO), and ozone (O_3). A high AQI implies relatively worse air pollution. Before 2013, the Chinese government monitored only SO_2, NO_2, and PM_{10}, which were used to construct the Air Pollution Index (*API)* and served as a summary measure of air quality. While the API and AQI are not directly comparable, they are highly correlated (Zheng et al., 2014). Similar to Dong et al. (2021), we use the API before 2013 and the AQI from 2013 in our sample and for notational simplicity, we refer to both as AQI in what follows and divide AQI by 1000 to eliminate the dimension influence.

Figure 1 shows the trend of AQI from 2000 to 2022 in China. During our sample period (2010–2022), the minimum and maximum values of the index ranged widely: 75.13 in 2022 and 222.80 in 2013, respectively. AQI shows noticeable fluctuations, with sharp increases observed in 2012, followed by a significant improvement in air quality after 2013. This improvement in 2013 can be largely attributed to policy measures such as the Action Plan on Air Pollution Prevention and Control (commonly referred to as the "Ten Measures for Air Pollution") introduced by the central government in 2013. We attribute the sudden increase in AQI in 2012 to the following factors: first, during this period, China experiences intensified air pollution due to rapid industrialization, urbanization, and increased coal consumption in key regions. These activities result in heightened levels of particulate matter and other pollutants, contributing to the observed spike in AQI (Genc et al., 2012). Second, in 2012, China began implementing more comprehensive air quality monitoring systems, including monitoring for $PM_{2.5}$ (fine particulate matter), which was

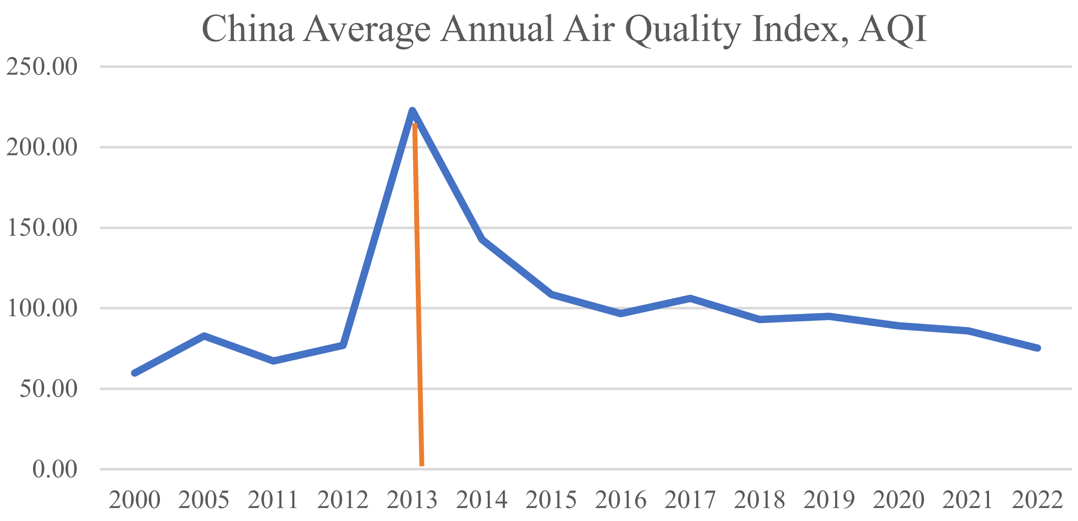

FIGURE 1 The time trend of China's average annual air quality index (AQI). The figure presents the time trend of China's average annual AQI from 2000 to 2022.

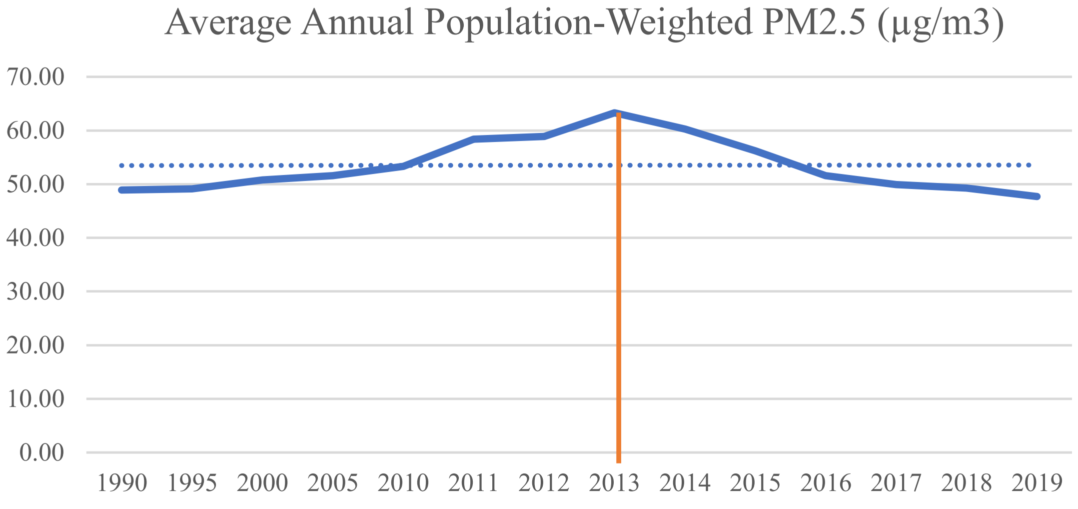

FIGURE 2 The time trend of China's average annual population-weighted PM2.5 (μg/m^3). The figure presents the time trend of China's average annual population weighted PM2.5 (μg/m^3) from 1990 to 2019.

previously not accounted for in the AQI calculations. This likely caused an apparent spike in AQI readings (Chen et al., 2013). Third, increased public and policy attention plays a pivotal role. The severe smog episodes, particularly the infamous “airpocalypse” in Beijing, draw significant concern from both the public and policymakers. This led to more transparent reporting of air quality data (He et al., 2016).

Figure 2 shows the trend of average annual population-weighted $PM_{2.5}$ (μg/m^3), similar to AQI's. Figure 3. presents the average air quality (AQI) for each province from 2010 to 2022. It is evident that the northern provinces experience higher levels of air pollution than the southern provinces. Table A2, Appendix A, provides summary statistics for the average annual AQI for each province during our sample period. We can see that the five heaviest polluted regions are Hebei, Henan, Shanxi, Tianjin, and Shanxi, and the five least polluted regions are Hainan, Tibet, Yunnan, Guizhou, and Fujian.

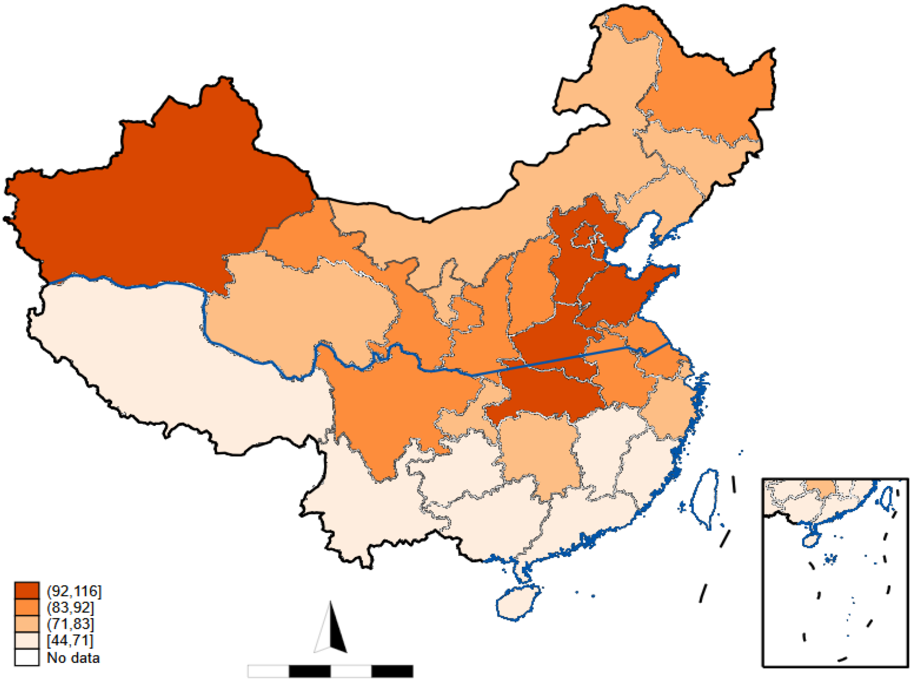

FIGURE 3 Average air quality index (AQI) between 2010 and 2022.

Data on AQI, API, and $PM_{2.5}$ are all city-level indexes obtained from the China Stock Market and Accounting Research (CSMAR).

3.2.2 | Firm-level air pollution exposure

We measure a firm's exposure to abnormal air pollution changes by regressing a stock's excess return on the Fama–French three factors and the air pollution anomaly variable. Specifically, we estimate the following time-series regression for stock *i*:

$$R_{i,t} - r_{f,t} = \alpha + \beta_{i,t}^{mkt} MKT_t + \beta_{i,t}^{smb} SMB_t + \beta_{i,t}^{hml} HML_t + \beta_{i,\ t}^{aqi} AQI\,Anomaly_t + e_t \quad (1)$$

where, $R_{i,t}$ is the contemporaneous return on firm *i* in month *t*, $r_{f,t}$ is the risk-free rate in month *t*. MKT_t, SMB_t, and HML_t are three Fama–French factors: the excess market returns, the factors small-minus-big, and the factors high-minus-low in month *t*, respectively. $AQI\,Anomaly_t$ is the abnormal AQI for each listed firm's headquarter city in month *t*. We define the abnormal AQI of each firm as the difference between $AQI_{i,t}$ of a firm *i* on month *t* and the average of AQI for all cities in the same month over the sample period. As the levels of AQI in the same city over the sample period differed drastically due to policy changes, our measure ensures that the return exposures only capture the impacts of the abnormal AQI within the same year or the same month, which makes the abnormal AQI more accurate and stricter. Using a 60-month rolling window, we measure air pollution sensitivity, $\beta_{i,t}^{aqi}$ from Equation (1). Then we average monthly data to obtain annual air pollution sensitivity, $\beta_{i,y}^{aqi}$. Finally, we use the absolute value of $\beta_{i,y}^{aqi}$ ($\left|\beta_{i,y}^{aqi}\right|$) to measure the firm's air pollution exposure (*AQI exposure*) following Nagar et al. (2019), as we do not know whether positive or negative sensitivities are more important for investors or have any expectation about whether a given firm will be negatively or positively affected by abnormal AQI over time.[10] Figure 4 presents the average air

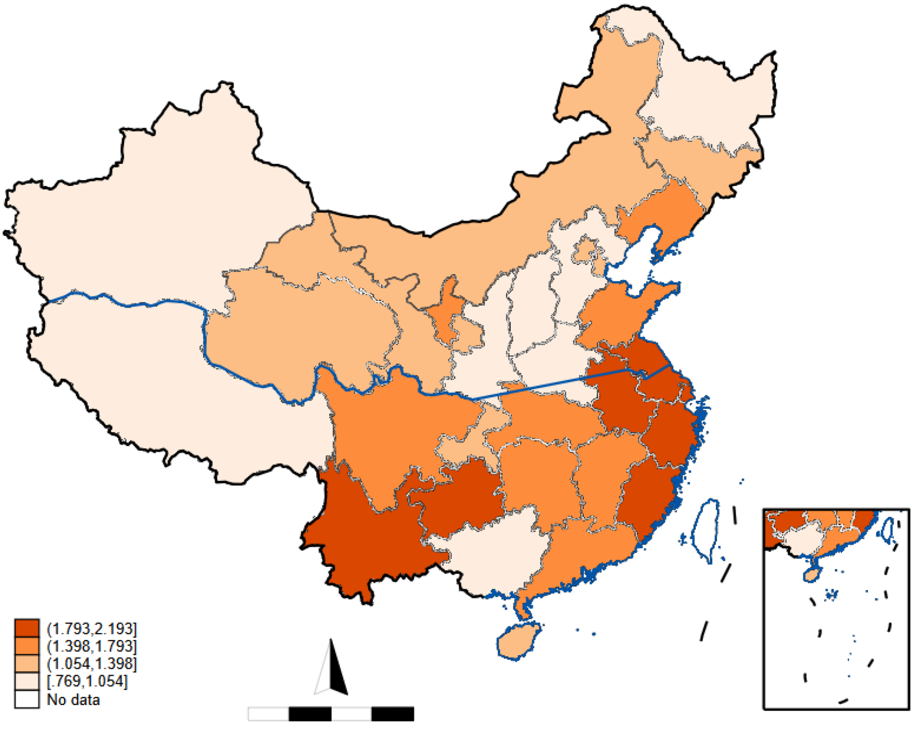

FIGURE 4 Average air pollution exposure (AQI exposure) between 2010 and 2022.

pollution exposure (*AQI exposure*) for each province from 2010 to 2022. It is evident that the southern provinces experience higher levels of air pollution exposure than the northern provinces on average. To avoid the influence of outliers, we winsorize *AQI exposure* ($\left|\beta_{i,y}^{aqi}\right|$) at the 1% level.

3.2.3 | Firm-level adjusted air pollution exposure

Table 1 shows the distribution of AQI exposure ($\left|\beta_{i,y}^{aqi}\right|$) by province. Since exposure captures a firm's sensitivity to air pollution changes perceived by investors, the underlying assumption of such exposure estimation is that stock prices would at least partially reflect the potential impact of abnormal air pollution changes on firm value. While high AQI (low AQI) is expected to result in high (low) exposures, we find that firms in southern provinces (or less-polluted provinces) are generally more sensitive to air pollution than those in northern provinces (or more-polluted provinces) in Table 1 and Figure 4. Table 2 presents the distribution of AQI exposure across various industries. Industries such as steel mills, chemical plants, coal-fired power plants, mining, transportation, and construction are significant contributors to air pollution. These sectors, often located in regions with high AQI levels, are inherently associated with highly polluting production processes. As a result, investors perceive that the value of firms in these industries is closely tied to their environmentally intensive operations. Given the unavoidable nature of these processes, investor's response to air pollution is more likely to be lower, resulting in low exposures. In contrast, firms in the education, scientific research, technical service, accommodation, and food industries are more sensitive to air pollution. These industries rely heavily on clean and conducive environments for their operations, as their core activities revolve around humans—students, researchers, tourists, travelers and hospitality workers—who are particularly susceptible to the effects of air pollution. Therefore, poor air quality directly impacts their health, leading to increased

TABLE 1 Distribution of air pollution exposure (AQI exposure) by province.

Province_Chinese	Southern or Northern province	Province_English	*N*	Mean	Province_Chinese	Southern or Northern province	Province_English	*N*	Mean
贵州省	Southern	Guizhou Province	132	2.193	辽宁省	Northern	Liaoning Province	260	1.793
上海市	Southern	Shanghai	1116	1.990	山东省	Northern	Shandong Province	971	1.636
江苏省	Southern	Jiangsu Province	2243	1.947	宁夏回族自治区	Northern	Ningxia Hui	24	1.491
福建省	Southern	Fujian Province	605	1.884	天津市	Northern	Tianjin	243	1.360
安徽省	Southern	Anhui Province	532	1.879	青海省	Northern	Qinghai Province	33	1.341
浙江省	Southern	Zhejiang Province	2338	1.840	内蒙古自治区	Northern	Inner Mongolia	107	1.281
云南省	Southern	Yunnan Province	113	1.827	甘肃省	Northern	Gansu Province	115	1.262
湖北省	Southern	Hubei Province	346	1.767	吉林省	Northern	Jilin Province	99	1.254
江西省	Southern	Jiangxi Province	204	1.737	北京市	Northern	Beijing	1709	1.123
四川省	Southern	Sichuan Province	468	1.726	陕西省	Northern	Shaanxi Province	219	1.054
广东省	Southern	Guangdong Province	3050	1.546	西藏自治区	Northern	Tibet	34	1.030
湖南省	Southern	Hunan Province	503	1.530	河南省	Northern	Henan Province	426	0.970
海南省	Southern	Hainan Province	68	1.398	河北省	Northern	Hebei Province	292	0.961
重庆市	Southern	Chongqing	190	1.098	山西省	Northern	Shanxi Province	114	0.911
广西壮族自治区	Southern	Guangxi	131	1.008	新疆维吾尔自治区	Northern	Xinjiang Uygur	154	0.888
					黑龙江省	Northern	Heilongjiang Province	114	0.769

Note: This table reports the distribution of AQI exposure by province in our sample period (The southern and northern provinces are divided by the Qinling-Huai River (QH) heating policy. The Huai River splits China into northern and southern parts, and China's central government provides free winter heating only in cities north of the Huai River (Lepori, 2016; Li et al., 2021).

TABLE 2 Distribution of air pollution exposure (AQI exposure) by industry.

Industry	*N*	Mean	Median	Min	Max	STD	Q1	Q3	Skew.
Education	13	2.240	0.878	0.006	11.544	3.938	0.506	1.187	1.881
Scientific research, technical service and geologic examination industry	268	2.142	1.116	0.001	11.544	2.666	0.483	2.464	2.060
Accommodation and food industry	1586	1.876	1.078	0.001	11.544	2.357	0.477	2.152	2.410
Manufacturing industry	12,526	1.642	0.876	0.000	11.544	2.198	0.376	1.872	2.688
Leasehold and business service industry	159	1.578	1.075	0.023	11.544	1.776	0.581	1.995	3.123
Traffic, storage and mail business	303	1.421	0.802	0.000	11.544	1.851	0.424	1.648	3.268
Cultural, physical and entertainment industry	197	1.401	0.978	0.054	11.003	1.528	0.426	1.800	2.998
Water conservancy, environment and public institution management	223	1.394	0.753	0.003	11.544	1.898	0.288	1.603	2.791
Farming, forestry, animal husbandry and fishery	182	1.286	0.725	0.003	10.555	1.592	0.324	1.623	2.732
Information transfer, computer service and software industry	276	1.235	0.787	0.001	11.544	1.617	0.397	1.429	3.701
Production and supply of electric power, gas and water	234	1.226	0.623	0.004	11.544	2.124	0.247	1.141	3.684
Public administration and social organization	7	1.191	0.994	0.736	2.439	0.583	0.840	1.243	1.598
Construction industry	473	1.153	0.653	0.000	11.544	1.754	0.302	1.250	3.911
Sanitation, social security and social welfare industry	40	1.138	0.705	0.022	7.787	1.444	0.347	1.255	2.948
Neighborhood services and other service industry	4	1.085	1.123	0.578	1.515	0.401	0.782	1.387	−0.276
Wholesale and retail trade	20	0.968	0.465	0.007	10.555	2.275	0.246	0.754	4.022
Realty business	103	0.923	0.555	0.010	8.061	1.194	0.251	1.113	3.475
Total	16,952	1.610	0.871	0.000	11.544	2.163	0.374	1.830	2.746

Note: This table reports the distribution of AQI exposure by industry in our sample period.

absenteeism, reduced productivity, and diminished service delivery. Customers of these industries, such as students, tourists, or diners, are more likely to avoid areas with poor air quality, leading to decreased demand and reduced revenue. For investors, these industries' dependence on customer footfall and workforce productivity makes them especially sensitive to air pollution risks. Investors recognize that a decline in air quality can directly impact operational performance and financial returns, increasing AQI exposure in their assessments. While these industries are not traditionally polluters, they are significantly affected by air quality due to their reliance on customer behavior and environmental conditions. Therefore, firms in these sectors face greater sensitivity to air pollution exposure compared to firms in heavily polluting industries. High-pollution sectors often incorporate such risks into their operational strategies, whereas cleaner sectors experience more pronounced disruptions when air quality deteriorates. Table 3, Panel A shows that the mean (median) of AQI exposures for non-polluting and polluting firms are 1.667 (0.900) and 1.460 (0.802), respectively. In addition, the mean (median) of AQI exposures for firms located in less-polluted provinces and polluted provinces are 1.692 (0.941) and 1.530 (0.806), respectively, as reported in Panel B. The *t*-test (*Wilcoxon* test) shows a significant difference in mean (median) in both panels.[11]

TABLE 3 Mean and median difference of AQI exposure by industry and province.

Panel A: *t*-test and Wilcoxon test by heavy polluted industry						
	Non-polluters		**Polluters**		**Diff**	***t*-value**
	N	Mean	*N*	Mean		
t-test	12,348	1.667	4604	1.460	0.207***	5.54
	N	Median	*N*	Median		
Wilcoxon test	12,348	0.900	4604	0.802	0.098***	0.00
Panel B: *t*-test and Wilcoxon test by heavy polluted provinces						
	Less-polluted provinces		**Polluted provinces**		**Diff**	***t*-value**
	N	Mean	*N*	Mean		
t-test	8440	1.692	8512	1.530	0.162***	0.00
	N	Median	*N*	Median		
Wilcoxon test	8440	0.941	8512	0.806	0.135***	0.00

Note: This table reports the mean and median difference of AQI exposure by industry and province. In Panel A, dummy variable that equals 1 if firm *i* belongs to the polluting industries, and 0 otherwise. Categorizations of these industries follow the CSRC Listed Company Industry Classification Guidelines (2012). In Panel B, dummy variable equals 1 if firm *i* is located in the heavily polluted provinces, and 0 otherwise. Categorizations of the heavily or not heavily polluted provinces follow the rules that are above and below the median level of the AQI index of all provinces in our sample.

To construct our main independent variable—the adjusted air pollution exposure (*A_AQI exposure*)—we account for two key factors simultaneously. First, we consider local air pollution levels. Air pollution is an economic 'bad' and represents a negative externality, meaning that a zero or very low AQI is always desirable. Second, firms operating in different industries and locations experience varying levels of exposure to local air pollution. We measure firm-level air pollution exposure from the perspective of investors, utilizing the Fama–French three-factor model to capture their perceptions. However, this approach fails to fully account for the intrinsic negative externalities of air pollution. Grouping firms solely by air pollution levels or exposure metrics may lead to misrepresentation, as firms in the same location can have differing exposures, and firms with similar exposures in regions with varying air quality should not be treated uniformly. To address this, we construct an adjusted air pollution exposure variable by multiplying the absolute value of firm-level AQI exposure (*AQI exposure*) with city-level AQI (*AQI*).[12] This measure captures both individual exposure and regional air quality, offering a more comprehensive assessment of air pollution's effects on R&D investments. Formally,

$$\text{Adjusted air pollution exposure (A\_AQI exposure)} = \left|\beta_{i,y}^{aqi}\right| \times AQI_{i,y} \tag{2}$$

Such a measure ensures that two firms with very high $\left|\beta_{i,y}^{aqi}\right|$, one from a high AQI city and the other from a low AQI city, are not in the same group. A firm from a high AQI city with a high $\left|\beta_{i,y}^{aqi}\right|$ is differentiated more accurately from a firm from a low AQI city with a high $\left|\beta_{i,y}^{aqi}\right|$. Similarly, a firm from a high AQI city with a low $\left|\beta_{i,y}^{aqi}\right|$ is differentiated more accurately from a firm from a low AQI city with a low $\left|\beta_{i,y}^{aqi}\right|$. In other words, adjusted AQI exposure captures both exposure to abnormal air pollution and AQI levels, confirming heterogeneity among firms' exposure to AQI.

3.2.4 | Corporate innovation investment

Following Chemmanur et al. (2019) and Mukherjee et al. (2017), we measure corporate innovation investment using R&D expenses scaled by total assets (*R&D_Assets*). To facilitate the interpretation of the regression coefficients, we multiply *R&D_Assets* by 100.

3.3 | Baseline model

To test the impact of adjusted air pollution exposure on corporate innovation investment, we propose the following baseline regression model:

$$Innovation_{i,y} = \alpha_0 + \beta_1 \times adjusted\,air\,pollution\,exposure_{i,y} + \gamma \times Controls_{i,y} + Firm + Year + \varepsilon_{i,y} \tag{3}$$

where i stands for firms, and y denotes years. $Innovation_{i,y}$ refers to the corporate innovation investment of firm i in year y, measured by the R&D expenditure to total assets of the firm. $Adjusted\,air\,pollution\,exposure_{i,y}$ is measured by $\left|\beta_{i,y}^{aqi}\right| \times AQI_{i,y}$. Following Cui et al. (2021) and Xu (2020), we control for some firm characteristics ($Controls_{i,t}$) that may affect innovation investment, including firm size (*Size*), return on assets (*ROA*), growth rate of sales (*Growth*), firm financial leverage (*Lev*), the ratio of market value to book value of assets (*Tobin's Q*), managerial ownership (*Mshare*), financial constraints index (*KZ* index), the top one major shareholding (*Top1*), independent directors' ratio (*IndepR*), the ratio of fixed assets (*Fixed*), number of board members (*BoardSize*), *Dual*, *Big 4*, state-owned enterprise (*SOE*) and polluting industries (*Polluter*). The definitions of the variables are provided in Table A1, Appendix A. All continuous variables are winsorized at the top and bottom 1% to mitigate the concern of outliers.

4 | EMPIRICAL RESULTS

4.1 | Descriptive statistics

We present descriptive statistics, including the mean, median, minimum, maximum, standard deviation, first quartile (*Q1*), and third quartile (*Q3*) value of variables in Table 4. As shown in Table 4, the maximum and minimum values of *R&D_Assets* are 11.650 percent and 0.010 percent, and the average value of *R&D_Assets* is 2.610 percent. These align with previous studies, such as Cui et al. (2021). Notably, the mean of *AQI exposure* is 1.610, and the median is 0.870. The mean and median for *A_AQI exposure* are 0.120 and 0.070, respectively. Regarding the control variables, the average firm size is 22.08, the average *ROA* is 5.00%, and the average leverage ratio is 38%. The average fixed assets investment is 19.7%. Approximately 35% of the CEOs in our sample are also chairmen, and the top major shareholders, on average, hold 33% of firm stocks. The average board size consists of approximately 8 (log = 2.10) members, 38% of whom are independent directors, consistent with the China Securities Regulatory Commission (CSRC) requirements on board independence. The distributions of the control variables are generally similar to those reported in previous research (Cui et al., 2021; Wen et al., 2022).

4.2 | Baseline results

Table 5 presents the baseline regression results using firm and year fixed effects, with robustness checks incorporating industry, province, and year fixed effects, and clustering standard errors at the firm level (column 5). In columns (1) and (2), the coefficients on *AQI* and *AQI exposure* are statistically insignificant, providing preliminary support for the notion that these variables alone do not exert a consistent or significant influence on corporate innovation investment. In column (3), the coefficient on adjusted AQI exposure (*A_AQI exposure*) is −0.109 and statistically significant at the 10% level, implying that adjusted AQI exposure negatively affects the corporate innovation investment. When controlling simultaneously for *AQI* and *AQI exposure* in column (4), the coefficient on *A_AQI exposure* becomes larger (−0.484) and significant at the 5% level, reinforcing the robustness of the finding. Furthermore, when estimating the model with industry, province, and year fixed effects as well as clustering standard errors at the firm level, the coefficient on *A_AQI exposure* remains statistically significant, underscoring the robustness of the finding

TABLE 4 Summary statistics.

Variable	*N*	Mean	Median	Min	Max	STD	*Q1*	*Q3*	Skew.
R&D_Assets	16, 952	2.610	2.190	0.010	11.650	2.120	1.240	3.370	1.770
A_AQI exposure	16, 952	0.120	0.070	0.000	1.680	0.170	0.030	0.140	3.030
AQI	16, 952	0.080	0.080	0.020	0.250	0.020	0.060	0.090	1.190
AQI exposure	16, 952	1.610	0.870	0.000	11.540	2.160	0.370	1.830	2.750
Size	16, 952	22.080	21.890	19.520	26.430	1.220	21.220	22.700	1.000
ROA	16, 952	0.050	0.051	−0.400	0.250	0.070	0.020	0.080	−1.480
Lev	16, 952	0.380	0.370	0.030	0.920	0.190	0.230	0.520	0.330
Growth	16, 952	0.190	0.130	−0.660	4.330	0.370	0.000	0.290	3.410
Tobin's Q	16, 952	2.180	1.760	0.800	17.730	1.370	1.340	2.520	2.850
KZ	16, 952	0.776	1.059	−6.227	5.037	2.144	−0.377	2.239	−0.788
Top 1	16, 952	0.330	0.310	0.080	0.750	0.140	0.220	0.430	0.550
BoardSize	16, 952	2.100	2.200	1.610	2.710	0.190	1.950	2.200	−0.360
IndepR	16, 952	0.380	0.360	0.290	0.600	0.050	0.330	0.430	1.120
Dual	16, 952	0.350	0.000	0.000	1.000	0.480	0.000	1.000	0.640
Mshare	16, 952	0.190	0.110	0.000	0.710	0.210	0.000	0.360	0.750
Fixed	16, 952	0.197	0.171	0.002	0.714	0.139	0.089	0.274	0.951
Big 4	16, 952	0.050	0.000	0.000	1.000	0.220	0.000	0.000	4.000
Listage	16, 952	1.780	1.950	0.000	3.090	0.800	1.390	2.400	−0.600
SOE	16, 952	0.210	0.000	0.000	1.000	0.400	0.000	0.000	1.460
Polluter	16, 952	0.270	0.000	0.000	1.000	0.440	0.000	1.000	1.030
Inv_PAT_APP	13, 808	0.660	0.000	0.000	6.974	1.012	0.000	1.099	1.842

Note: This table presents the summary statistics for the sample: mean, median, minimum, maximum, standard deviation, 25%,75%, and skewness of variables. *R&D_Assets* is the ratio of R&D expenditure to total assets of each firm and then multiplied by 100. *A_AQI exposure* is the interaction term that takes a value of AQI × AQI exposure. *AQI* is the yearly average Air Quality Index (AQI) in which a firm is headquartered. *AQI exposure* is the absolute value of AQI beta calculated based on the Fama–French three-factor model. The definitions of the variables are provided in Table A1, Appendix A. We winsorize the data at the 1% and 99% levels.

across alternative specifications. In the following tests, we follow Lai et al. (2023) by including year, industry, and province fixed effects and clustering standard errors at the firm level to account for potential time-varying confounders across different dimensions. Based on column (3), a one standard deviation increase in adjusted AQI exposure (SD = 0.170) is associated with a 0.71% decline in R&D intensity (*R&D_Assets*), indicating both statistically and economically meaningful effects of adjusted air pollution exposure on corporate innovation investment. Our results support the real option theory that if the investment is irreversible, the uncertainty increases the value of the option to wait, and firms can avoid sunk costs by deferring risky investment projects (Bulan, 2005; Gulen & Ion, 2016). Furthermore, Figure 5 shows a clear negative correlation between *A_AQI exposure*, *AQI exposure*, and *R&D_Assets*. The findings support our baseline results, indicating that adjusted air pollution exposure negatively impacts corporate innovation investment.

The coefficients on the control variables are generally consistent with those reported in relevant studies (Cui et al., 2021; Wen et al., 2022). For example, the coefficients on *Growth*, *Tobin's Q*, and *Mshare* are all positive and significant at the 1% level, suggesting that firms with higher growth rate and higher market value are more likely to invest in innovative projects. The positive effect of managerial ownership on innovation implies that managerial ownership promotes innovative expenditures because innovation can increase a firm's long-run value. Overall, the results

TABLE 5 Baseline regressions: adjusted air pollution exposure and corporate innovation investment.

Variables	R&D_Assets (1)	R&D_Assets (2)	R&D_Assets (3)	R&D_Assets (4)	R&D_Assets (5)
A_AQI exposure			−0.109*	−0.484**	−0.478**
			(−1.79)	(−2.28)	(−2.20)
AQI	−0.664			0.212	−0.477
	(−0.68)			(0.20)	(−0.21)
AQI exposure		−0.005		0.032*	0.021
		(−1.10)		(1.86)	(1.42)
Size	0.010	0.010	0.012	0.013	0.001
	(0.10)	(0.12)	(0.10)	(0.11)	(0.03)
ROA	−0.077	−0.078	−0.076	−0.074	1.701**
	(−0.51)	(−0.52)	(−0.51)	(−0.50)	(2.66)
Lev	−0.142	−0.144	−0.141	−0.140	0.012
	(−1.47)	(−1.48)	(−1.46)	(−1.44)	(0.97)
Growth	0.046**	0.046**	0.046**	0.046**	0.032
	(2.24)	(2.26)	(2.27)	(2.26)	(0.29)
Tobin's Q	0.072***	0.072***	0.072***	0.072***	0.334***
	(8.79)	(8.83)	(8.86)	(8.82)	(8.13)
KZ	−0.042***	−0.042***	−0.042***	−0.041***	−0.022**
	(−6.48)	(−6.44)	(−6.42)	(−6.43)	(−1.98)
Top1	0.060	0.061	0.062	0.066	−0.947***
	(0.37)	(0.38)	(0.39)	(0.41)	(−3.14)
Board	0.444***	0.444***	0.445***	0.446***	0.158**
	(4.90)	(4.90)	(4.91)	(4.92)	(2.67)
IndepR	0.242	0.240	0.238	0.237	0.357
	(0.88)	(0.87)	(0.86)	(0.86)	(0.73)
Dual	0.024	0.024	0.023	0.023	0.098**
	(0.97)	(0.97)	(0.96)	(0.94)	(2.93)
Mshare	0.198**	0.196**	0.195*	0.196*	0.354***
	(1.97)	(1.96)	(1.95)	(1.95)	(3.93)
Fixed	0.612	0.612	0.612	0.617	−1.631***
	(1.47)	(1.49)	(1.48)	(1.48)	(−10.92)
Big4	0.230***	0.228***	0.229***	0.231***	0.451**
	(2.77)	(2.75)	(2.75)	(2.78)	(2.29)
List age	−0.087***	−0.103***	−0.113***	−0.109***	−0.207***
	(−2.59)	(−2.83)	(−3.09)	(−2.98)	(−6.68)
SOE	−0.094	−0.094	−0.094	−0.093	0.099
	(−1.64)	(−1.63)	(−1.63)	(−1.63)	(0.94)
Polluter	0.098	0.099	0.099	0.096	−0.315***
	(1.05)	(1.06)	(1.06)	(1.03)	(−14.31)
Constant	10.879***	10.869***	10.899***	10.877***	2.009**
	(18.85)	(18.99)	(19.04)	(18.81)	(2.57)

TABLE 5 (Continued)

Variables	R&D_Assets (1)	R&D_Assets (2)	R&D_Assets (3)	R&D_Assets (4)	R&D_Assets (5)
Firm	Yes	Yes	Yes	Yes	No
Year	Yes	Yes	Yes	Yes	Yes
Industry	No	No	No	No	Yes
Province	No	No	No	No	Yes
S.E. Cluster	No	No	No	No	Firm
N	16,393	16,393	16,393	16,393	16,952
Adj R^2	0.864	0.864	0.863	0.864	0.275

Note: This table reports the results of baseline regressions. It shows the impact of adjusted air pollution exposure on corporate innovation investment. The dependent variables are *R&D_Assets*, measured by R&D expenditure to total assets of each firm and then multiplied by 100 in $year_t$. The main independent variable is *A_AQI exposure*, measured by the *AQI* × *AQI exposure*. Definitions of variables are presented in Table A1, Appendix A. The *t*-statistics are reported in parentheses. The superscripts *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

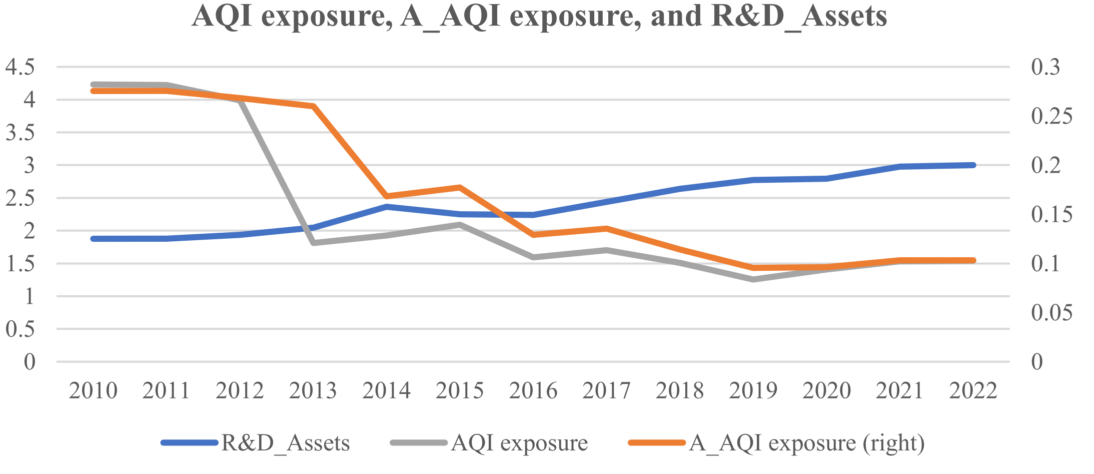

FIGURE 5 The time trend for AQI exposure, A_AQI exposure, and R&D_Assets. The figure presents the time-trend for China's AQI exposure, A_AQI exposure, and R&D_Assets from 2010 to 2022. The definitions of these three variables are provided in Table A1, Appendix A.

in Table 5 support our Hypothesis *1b*, that adjusted air pollution exposure has a negative impact on corporate innovation investment.

To get a deeper understanding of our adjusted exposure measure, *A_AQI exposure*, we re-run the baseline regressions on the absolute value of AQI exposure by creating sub-samples based on AQI quantiles, where *AQI_1* stands for First quantile (low AQI index), and *AQI_5* stands for Last quantile (high AQI index). Results reported in Table A4 (Panel A), Appendix A, shows that none of the AQI exposure coefficient estimates are statistically significant, confirming our earlier findings that AQI exposure, by itself, does not show any significant impact on R&D. We further substantiate the findings in Panel B, where four sub-samples are created based on the median value of both AQI and the absolute value of exposures: High AQI-High exposure, High AQI-Low exposure, Low AQI-High exposure, and Low AQI-Low exposure. The coefficient estimates of *A_AQI* exposure are negative and statistically significant except for High AQI-High exposure.

4.3 | Endogeneity tests

In this section, we conduct three methods to address potential endogeneity issues: (1) controlling for multiple fixed effects and macroeconomic uncertainty, (2) propensity score matching (PSM) method, and (3) staggered difference-in-difference method.

4.3.1 | Multiple fixed effects and macroeconomic uncertainty

To mitigate potential problems due to firm-specific, time-invariant heterogeneity and headquarters change, we re-estimate the baseline regression while controlling for firm, industry, province, and year-fixed effects (Lai et al., 2023). In addition, we add the GDP growth and GDP per capita as additional controls in Equation (2) and re-estimate the impact of adjusted air pollution exposure on corporate innovation investment. The results in Table 6 show that the estimated coefficients on *A_AQI exposure* are all significantly negative, at least at the 10% level. This indicates that our baseline results are robust after controlling for multiple fixed effects and macroeconomic uncertainty.

4.3.2 | Propensity score matching approach

To substantiate the observed effects of adjusted air pollution exposure on corporate innovation investment, we generate an adjusted air pollution exposure dummy variable based on its median level, which equals 1 if the firm faces high adjusted air pollution exposure and 0 otherwise. We assume there may be observable differences between firms with different adjusted air pollution exposure levels. Thus, we use the propensity score matching approach to resolve this issue.

The results from the pre-matched logistic model are presented in column (1), Panel A of Table 7. Then, by applying the one-to-one nearest-neighbor propensity score approach, each firm with high adjusted air pollution exposure is matched with the most similar firm with low adjusted air pollution exposure. To improve the matching accuracy, we exclude the pairs with a propensity score difference larger than 1%. We conduct two diagnostic tests to ensure matching accuracy. First, we re-conduct the logistic analysis using the propensity score-matched sample. The results are reported in column (2), Panel A of Table 7. All the coefficients on independent variables in the post-matched logistic model become much smaller and insignificant, suggesting no observable difference between treatment and control after matching. Second, we compare the characteristics of firms with high and low adjusted air pollution exposure using *t*-tests. The pre-matched *t*-test results are reported in Panel A of Table A5, Appendix A, which reveals that firms are significantly different in their characteristics depending on whether they face high or low adjusted air pollution exposure. The post-matched *t*-test results are reported in Panel B, which show no significant difference between firms with high and low adjusted air pollution exposure in the propensity score-matched sample.

Using the propensity score-matched sample, we re-estimate the baseline regression controlling for industry, province, and year-fixed effects. The results reported in Panel B of Table 7 show that the coefficients on *A_AQI exposure* are −0.122 and −0.083 in columns (1) and (2) and are statistically significant at 5% and 1%, respectively. In general, the propensity score matching results confirm that the results of Table 5 are robust (Table A7).

4.3.3 | Staggered difference-in-difference analysis

In the above analysis, we confirm that there is a significant negative relationship between adjusted air pollution exposure and the corporate innovation investment, addressing endogeneity concerns through the inclusion of control variables, fixed effects, and propensity score matching (PSM) approach. In this section, we further employ a

TABLE 6 Endogeneity test: multiple fixed effects and macroeconomic uncertainty.

Variables	*R&D_Assets* (1)	*R&D_Assets* (2)	*R&D_Assets* (3)
A_AQI exposure	−0.110*	−0.500**	−0.496**
	(−1.81)	(−2.36)	(−2.33)
AQI		−0.039	−0.027
		(−0.04)	(−0.03)
AQI exposure		0.034*	0.033
		(1.94)	(1.71)
GDP growth			−0.064
			(−0.12)
GDP per capita			0.127
			(0.41)
Constant	11.612***	11.609***	11.600***
	(20.08)	(19.88)	(19.81)
Controls	Yes	Yes	Yes
Firm	Yes	Yes	Yes
Year	Yes	Yes	Yes
Industry	Yes	Yes	Yes
Province	Yes	Yes	Yes
N	16,393	16,393	16,393
Adj R^2	0.664	0.664	0.669

Note: This table reports the results of endogeneity test on the baseline results. We control the firm, year, province, and industry fixed effects and also control the macroeconomic uncertainty based on the Equation (2). The *t*-statistics are reported in parentheses. The symbol *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

staggered difference-in-differences (DID) approach to validate our baseline results by examining an exogenous event: the implementation of the Action Plan for Air Pollution Prevention and Control and the Action Plan for Continuous Improvement of Air Quality.[13]

The Action Plan for Air Pollution Prevention and Control (2013–2017), launched in 2013, was China's first comprehensive national initiative to combat air pollution. The plan aimed to address severe air quality issues by reducing particulate matter concentrations and improving overall air quality, particularly in regions experiencing the highest levels of pollution. It prioritized the Beijing-Tianjin-Hebei region, the Yangtze River Delta, and the Pearl River Delta, where industrial emissions, coal combustion, and vehicle exhaust significantly contributed to pollution levels. The plan introduced a range of measures, including promoting clean energy alternatives to coal, implementing stricter vehicle emissions standards, enhancing industrial emissions controls, and encouraging the adoption of public transportation and green technologies. This plan marked a shift toward environmental accountability, with specific reduction targets set for cities and provinces.[14]

Building on the achievements of the 2013 plan, the Action Plan for Continuous Improvement of Air Quality (2018–Present) expanded the scope and scale of China's air quality initiatives. This plan broadened its focus to encompass a larger number of cities and regions, including economically developing areas in the Central Plains, Northeast China, and emerging industrial hubs. In 2018, it emphasized inter-city collaboration within key regions such as the Yangtze River Delta, Pearl River Delta, and Beijing-Tianjin-Hebei region, implementing regionally

TABLE 7 Endogeneity test: propensity scores matching analysis.

Panel A: Propensity score regression (logit model)			Panel B: Matched sample regression analysis	
	Pre-match (1)	Post-match (2)	(1)	(2)
Variables	Exposure dummy	Exposure dummy	*R&D_Assets*	*R&D_Assets*
A_AQI exposure			−0.122**	−0.083*
			(−2.51)	(−1.73)
AQI				−0.682
				(−0.46)
AQI exposure				−0.016
				(−1.51)
Size	−0.025***	−0.006	−0.050	−0.051
	(−5.31)	(−0.75)	(−1.36)	(−1.38)
ROA	0.117*	−0.140	1.684**	1.689**
	(1.83)	(−1.33)	(2.42)	(2.43)
Lev	0.115***	0.036	0.068	0.072
	(4.39)	(0.85)	(0.36)	(0.37)
Growth	0.039***	−0.007	0.040	0.042
	(3.68)	(−0.40)	(0.45)	(0.47)
Tobin's Q	0.018***	0.002	0.328***	0.328***
	(5.65)	(0.38)	(9.19)	(9.20)
KZ	0.181	0.079	−0.021**	−0.022**
	(1.72)	(1.03)	(−1.98)	(−2.01)
Top1	−0.078***	0.004	−1.466***	−1.466***
	(−2.78)	(0.08)	(−8.51)	(−8.53)
Board	−0.041	−0.033	−0.054	−0.052
	(−1.59)	(−0.79)	(−0.28)	(−0.27)
IndepR	−0.254	0.029	−0.412	−0.416
	(−1.23)	(0.20)	(−0.67)	(−0.68)
Dual	−0.013	−0.002	0.195***	0.195***
	(−1.63)	(−0.16)	(3.64)	(3.63)
Mshare	−0.026	0.021	0.482***	0.480***
	(−1.23)	(0.56)	(3.48)	(3.47)
Fixed	−0.012	−0.010	−1.631***	−1.631***
	(−0.34)	(−0.50)	(−13.09)	(−10.97)
Big4	−0.009	−0.001	0.429***	0.431***
	(−0.50)	(−0.03)	(3.30)	(3.31)
List age	−0.179***	0.004	−0.292***	−0.303***
	(−29.77)	(0.38)	(−5.99)	(−5.85)
SOE	−0.022*	−0.017	0.109	0.114*
	(−1.94)	(−0.96)	(1.62)	(1.67)
Polluter	−0.005	−0.018	−0.243***	−0.243***
	(−0.53)	(−1.22)	(−4.44)	(−4.44)

TABLE 7 (Continued)

Panel A: Propensity score regression (logit model)			Panel B: Matched sample regression analysis	
	Pre-match (1)	Post-match (2)	(1)	(2)
Variables	Exposure dummy	Exposure dummy	*R&D_Assets*	*R&D_Assets*
Constant	1.697***	0.917	1.809*	1.911*
	(13.16)	(0.34)	(1.81)	(1.91)
Industry	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes
Province	Yes	Yes	Yes	Yes
Observations	16,952	12,140	12,140	12,140
Pseudo R^2	0.133	0.028	0.295	0.296

Note: Table 7 presents the results of a propensity score matching analysis. We generate an adjusted air pollution exposure dummy variable based on the median level of exposure. Panel A reports the parameter estimates from the logit model used to estimate propensity scores. The adjusted air pollution exposure dummy is the dependent variable, which equals 1 if the firm faces high adjusted air pollution exposure and 0 otherwise. Panel B reports the results of re-estimating the baseline regression using the propensity score-matched sample. The dependent variable is the *R&D_Assets*. Definitions of variables are in Table A1, Appendix A. The *z*-statistics (*t*-statistics) are calculated based on robust standard errors and are reported in parentheses. The superscripts *, **, and ***indicate significance at the 10%, 5%, and 1% levels, respectively. More details about the PSM analysis are provided in Table A7.

coordinated air quality control measures to achieve comprehensive improvements. Since 2021, the plan has shifted its focus to region-based pollution control and the adoption of smart monitoring technologies to address pollution on a broader scale. This phase extends its efforts beyond major cities to include lower-tier cities in rapidly growing economic regions, as well as emerging industrial hubs and tourism destinations facing heightened pollution risks.[15]

We construct the staggered DID regression model as follows:

$$\begin{aligned} Innovation_{i,y} = {} & \alpha_0 + \beta_1 \times Adjusted\,air\,pollution\,exposure_{i,y} + \beta_2 \times Post_{i,y} + \beta_3 \\ & \times Aadjusted\,air\,pollution\,exposure_{i,y} \times Post_{i,y} + \gamma \times Controls_{i,y} + \varepsilon_{i,y} \end{aligned} \tag{4}$$

where i stands for firm, and y denotes year. $Innovation_{i,y}$ refers to the corporate innovation investment of firm i in year y, measured by the R&D expenditure to total assets of the firm. $Adjusted\,air\,pollution\,exposure_{i,y}$ is measured by $\left|\beta_{i,y}^{aqi}\right| \times AQI_{i,y}$. $Post_{i,y}$ is the dummy variable that takes the value of 1 if the firm's headquarters city is designated as a priority air quality monitoring city in a given year, and 0 otherwise. The effect of adjusted air pollution exposure on corporate innovation after the policy launch is represented by the coefficient estimate (β_3) on $Aadjusted\,air\,pollution\,exposure_{i,y} \times Post_{i,y}$.

The estimated results are shown in Table 8. The *Post* coefficient is significantly positive at the 1% level, indicating that cities designated for air pollution monitoring have promoted innovation within corporations. Our main focus is on the *A_AQI exposure* $\times$ *Post* coefficient, which measures the impact of adjusted air pollution exposure on innovation inputs of the companies following the implementation of the policy. Columns (1) and (2) both show that the DID coefficients are significantly positive at the 1% level, indicating that the launch of the Action Plan has mitigated the negative impact of adjusted air pollution exposure on innovation investments.

TABLE 8 Endogeneity test: staggered difference-in-difference approach.

Variables Model	*R&D_Assets* (1)	*R&D_Assets* (2)
A_AQI exposure	−0.428***	−0.670*
	(−3.74)	(−1.75)
Post	0.087**	0.135***
	(2.30)	(3.27)
A_AQI exposure × Post	0.455**	0.456**
	(2.26)	(2.57)
AQI		−2.545**
		(−2.37)
AQI exposure		0.022
		(0.74)
Constant	2.233***	2.379***
	(4.96)	(5.22)
Controls	Yes	Yes
Industry	Yes	Yes
Year	Yes	Yes
Province	Yes	Yes
S.E. Clustering	Firm	Firm
N	16,952	16,952
Adj R^2	0.284	0.284

Note: Table 8 presents the results of a staggered difference-indifference approach. We utilize the Action Plan for Air Pollution Prevention and Control, along with the Action Plan for Continuous Improvement of Air Quality, to examine whether air quality monitoring pilot cities could serve as a shock. The dependent variable is the *R&D_Assets*. $Post_{i,y}$ is the dummy variable that takes the value of 1 when the firm's headquarter city is designated as air quality monitoring city in a given year and 0 otherwise. The effect of adjusted air pollution exposure on corporate innovation after the policy launch is represented by the coefficient estimate on $Aadjusted\,air\,pollution\,exposure_{i,y} \times Post_{i,y}$. Definitions of variables are in Table A1, Appendix A. The *t*-statistics are reported in parentheses. The superscripts *, **, and ***indicate significance at the 10%, 5%, and 1% levels, respectively.

4.4 | Robustness checks

4.4.1 | Alternative measures of adjusted AQI exposure

In this section, as a robustness check, we reconstruct the adjusted AQI exposure measure using a 36-month rolling window. We control for industry, province, and year fixed effects to estimate Equation (2). Panel A of Table 9 shows that the coefficients on *A_AQI exposure* (36) are all significantly negative, at least at the 5% level in columns (1) and (2).

Second, we construct an alternative measure of industry adjusted air pollution exposure by replacing adjusted air pollution exposure in two steps. Since $\left|\beta_{i,t}^{aqi}\right|$ varies across industries, we measure the industry-adjusted exposure by subtracting the median[16] of exposure of industry *j* in month *t* $\left|\overline{\beta_{j,t}^{aqi}}\right|$ from the exposure of firm *i* of industry *j* in month *t* over the sample period, $\left|\beta_{i,j,t}^{aqi}\right|$. Formally,

$$\text{Monthly industry} - \text{adjusted exposure} = \left|\beta_{i,j,t}^{aqi}\right| - \left|\overline{\beta_{j,t}^{aqi}}\right| \tag{5}$$

TABLE 9 Robustness check: alternative measures of adjusted air pollution exposure.

	Panel A: Alternative adjusted air pollution exposure: *A_AQI exposure* (36)		Panel B: Alternative adjusted air pollution exposure: *Industry A_AQI exposure*		Panel C: Alternative adjusted air pollution exposure: $\left\|\beta_{i,t}^{aqi}\right\| \times \log(1+AQI_{i,y})$	
	R&D _Assets	*R&D _Assets*	*R&D _Assets*	*R&D _Assets*	*R&D _Assets*	*R&D _Assets*
Variables	**(1)**	**(2)**	**(1)**	**(2)**	**(1)**	**(2)**
A_AQI exposure (36)	−1.283***	−1.261**				
	(−5.16)	(−2.83)				
Industry A_AQI exposure			−0.218**	−0.413*		
			(−2.24)	(−1.85)		
$\left\|\beta_{i,y}^{aqi}\right\| \times \log(1+AQI_{i,y})$					−0.004**	−0.042**
					(−2.31)	(−2.51)
AQI		−0.705		−0.928		
		(−0.21)		(−0.42)		
$\log(1+AQI_{i,y})$						−0.134
						(−0.78)
AQI exposure (36)		−0.015				
		(−0.27)				
$\left\|\beta_{i,y}^{aqi}\right\|$ (AQI exposure)				0.016		0.175*
				(1.20)		(2.19)
Constant	1.578***	1.618	1.972***	2.014**	2.174***	3.385**
	(3.70)	(1.51)	(4.37)	(2.20)	(4.82)	(2.97)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Industry	Yes	Yes	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes	Yes	Yes
Province	Yes	Yes	Yes	Yes	Yes	Yes
S.E. Clustering	Firm	Firm	Firm	Firm	Firm	Firm
N	17,703	17,703	16,952	16,952	16,952	16,952
Adj R^2	0.283	0.283	0.275	0.275	0.282	0.308

Note: This table reports the results of robustness checks of the baseline results. In Panel A, we reconstruct the adjusted air pollution exposure measure using the 36-month rolling window, *A_AQI exposure* (36). In Panel B, we run the baseline results using the industry *A_AQI exposure*, which takes the value of industry-adjusted exposure (median) × AQI. In Panel C, we run the baseline results using the $\left|\beta_{i,t}^{aqi}\right| \times \log(1+AQI_{i,y})$ as alternative independent variable. The *t*-statistics are reported in parentheses. The symbols *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Then, we average monthly data to obtain absolute annual industry-adjusted exposure, $\left|\beta_{i,j,y}^{aqi}\right|$. Now, by multiplying this exposure with annual city-level AQI, we have industry A_AQI exposure $= \left|\beta_{i,j,y}^{aqi}\right| \times AQI_{i,y}$. We then re-run our baseline regression. Panel B of Table 9 shows that the coefficients on industry *A_AQI exposure* are significantly negative at least at the 10% level in columns (1) and (2).

Third, we use $\left|\beta_{i,y}^{aqi}\right| \times \log(1+AQI_{i,y})$ as alternative measure of adjusted air pollution exposure for a robustness check to mitigate any potential non-linearity between "exposure" and "pollution". Panel C of Table 9 shows that the coefficients on $\left|\beta_{i,y}^{aqi}\right| \times \log(1+AQI_{i,y})$ are both significantly negative at the 5% level in columns (1) and (2).

4.4.2 | Alternative measures of corporate innovation

Regarding the corporate innovation investment measurement, firstly, we use $R\&D\_Assets_{t+1}$ and *R&D_Sales* to replace the *R&D_Assets* as our dependent variables. The coefficients in Panels A and B of Table 10 on *A_AQI exposure* are still negative and significant, at least at the 10% level across all columns. The findings support our baseline results.

Secondly, Fang et al. (2014) suggest that compared with R&D investment—which measures observable innovation input—patenting activity is a good proxy for corporate innovation because it captures both innovation output and the efficiency of corporate innovation. We, therefore, use the number of invention patent applications during a fiscal year, $Inv\_PAT\_APP_{t+1}$, as the alternative measure of corporate innovation. Most of the invention patent application data used in this paper are obtained from the CSMAR and Chinese Research Data Services Platform (CNRDS) databases, and we manually collect missing patent application data from the patent query system of the State Intellectual Property Office. The maximum and minimum natural logarithm values of the patent are 6.974 and 0, with an average value of 0.660, which align with Jie et al. (2021). The results indicate that patent applications vary greatly across sample firms. As shown in Panel C of Table 10, *A_AQI exposure* is negatively associated with the number of patent applications in columns (1) and (2), at least the 5% level. The above results indicate that the negative impacts

TABLE 10 Robustness check: alternative measures of corporate innovation.

Panel A: $R\&D\_Assets_{t+1}$			**Panel B: R&D_Sales**		**Panel C:** $Inv\_PAT\_APP_{t+1}$	
	$R\&D\_Assets_{t+1}$	$R\&D\_Assets_{t+1}$	**R&D_Sales**	**R&D_Sales**	$Inv\_PAT\_APP_{t+1}$	$Inv\_PAT\_APP_{t+1}$
Variables	**(1)**	**(2)**	**(1)**	**(2)**	**(1)**	**(2)**
A_AQI exposure	−0.119**	−0.105*	−0.862***	−2.099*	−0.108***	−0.091**
	(−2.01)	(−1.73)	(−3.78)	(−1.90)	(−3.63)	(−2.49)
AQI		0.901		8.759		2.415*
		(0.44)		(1.60)		(1.89)
AQI exposure		0.077		0.151		−0.004
		(1.50)		(1.43)		(−0.59)
Constant	1.873**	1.904*	1.959**	−1.383	−4.068***	−4.192***
	(2.37)	(1.75)	(2.93)	(−0.66)	(−2.92)	(3.41)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Industry	Yes	Yes	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes	Yes	Yes
Province	Yes	Yes	Yes	Yes	Yes	Yes
S.E. Clustering	Firm	Firm	Firm	Firm	Firm	Firm
N	13,048	13,048	16,952	16,952	10,583	10,583
Adj R^2	0.260	0.260	0.260	0.345	0.202	0.203

Note: This table reports the results of the robustness check based on the baseline results. In Panel A, the dependent variable is $R\&D\_Assets_{t+1}$, measured by R&D expenditure to the total assets of each firm in $year_{t+1}$ (multiplied by 100). In Panel B, the dependent variable is *R&D_Sales*, measured by R&D expenditure to the sales of each firm. Panel C shows the impact of adjusted air pollution exposure on invention patent applications in the following fiscal year, $Inv\_PAT\_APP_{t+1}$. The main independent variable is adjusted air pollution exposure, measured by the $AQI \times AQI\ exposure$. Definitions of variables are presented in Table A1, Appendix A. The *t*-statistics are reported in parentheses. The superscripts *, **, and ***indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

of adjusted air pollution exposure on corporate innovation investment remain significant when using patenting activity as the proxy for corporate innovation.[17]

4.4.3 | Sub-samples with positive and negative AQI sensitivity (AQI beta)

To measure firm-specific sensitivity to air pollution shocks, we regress the Fama–French three-factor model by including an air pollution anomaly factor in Equation (1). The coefficient $\beta_{i,\,t}^{aqi}$ captures a firm's sensitivity to abnormal air pollution fluctuations. The sign of this coefficient (positive or negative) indicates the direction of the relationship between a firm's stock returns and abnormal changes in air quality, thereby reflecting the economic nature of the firm's exposure to pollution risk. A positive $\beta_{i,\,t}^{aqi}$ suggests that the firm's stock returns tend to increase with higher levels of air pollution. This typically applies to pollution-intensive firms (e.g., coal, steel) that benefit from either lax regulations or stable demand in polluted areas. Conversely, a negative $\beta_{i,\,t}^{aqi}$ implies that the firm's returns tend to decline as pollution worsens. This pattern is more common among environmentally sensitive or ESG-oriented firms, such as green technology companies or service-sector businesses (e.g., tourism), which face reduced consumer demand or increased costs during pollution episodes. While the sign of the sensitivity provides valuable economic interpretation, our primary focus is on the magnitude (e.g., the absolute value) of the coefficient to measure the intensity of a firm's exposure to air quality fluctuations (AQI exposure). This approach captures the extent of exposure regardless of its direction and avoids the issue of opposing effects canceling each other out in aggregate analyses (Nagar et al., 2019).

However, if there is an asymmetric effect of positive and negative sensitivities on the dependent variable, then such transformation in absolute value would not be captured in the regression. Thus, we divide the sample firms into two groups based on the original sign of $\beta_{i,y}^{aqi}$ and re-run the baseline regression:

Firms with positive sensitivities: $\left|\beta_{i,y}^{aqi}\right|$ when $\beta_{i,y}^{aqi} > 0$.

Firms with negative sensitivities: $\left|\beta_{i,y}^{aqi}\right|$ when $\beta_{i,y}^{aqi} < 0$.

The results are reported in Panels A and B of Table 11, which indicate that adjusted air pollution exposure negatively impacts corporate innovation investment regardless of whether the AQI sensitivity is originally positive or negative. In summary, the results of our baseline study remain robust, supporting our Hypothesis *1b* that adjusted air pollution exposure has a negative impact on corporate innovation investment.[18]

4.5 | Further analysis

4.5.1 | Mediation effects

To explain the relationship between adjusted air pollution exposure and corporate innovation investment, we propose that firms with high adjusted air pollution exposure would exacerbate their operational risk and financial distress and be more likely to take a "wait-it-out" decision (Bordo et al., 2016; Frijns et al., 2013). This could serve as a potential mechanism that supports the real options theory. This paper uses the net operating cash flow (*CF*) and debt financing cost (*Fincost*) to measure firms' operational risk and financial distress. Following Baron and Kenny (1986), we perform a series of mediation analyses. Prior literature has adopted this methodology to provide direct evidence on underlying channels in other settings (Lang et al., 2012; Tsang et al., 2014).

The mediation analysis requires the following three conditions to be met. First, the independent variable (*A_AQI exposure*) should significantly relate to the dependent variable (*R&D_Assets*). Second, the independent variable (*A_AQI exposure*) should significantly relate to the mediator variable (*CF* or *Fincost*). Finally, the dependent variable (*R&D_Assets*) is regressed on both the independent variable (*A_AQI exposure*) and the mediators (*CF* or *Fincost*). If the mediator variable mediates the association between adjusted air pollution exposure and corporate

TABLE 11 Sub-samples with positive and negative AQI sensitivity (AQI beta).

	Panel A: Positive AQI sensitivity (AQI beta) sample		Panel B: Negative AQI sensitivity (AQI beta) sample	
	R&D_Assets	R&D_Assets	R&D_Assets	R&D_Assets
Variables	(1)	(2)	(1)	(2)
A_AQI exposure	−0.244***	−0.879**	−0.202	−0.237*
	(−3.90)	(−2.19)	(−1.39)	(−1.82)
AQI		0.113		1.163
		(0.09)		(0.48)
AQI exposure		0.052		0.002
		(1.45)		(0.11)
Constant	2.429***	2.396***	1.552***	1.329***
	(4.73)	(4.49)	(4.59)	(3.69)
Controls	Yes	Yes	Yes	Yes
Industry	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes
Province	Yes	Yes	Yes	Yes
S.E. Clustering	Firm	Firm	Firm	Firm
N	8295	8295	8657	8657
Adj R^2	0.264	0.265	0.285	0.287

Note: This table reports the results of further robustness checks on the baseline results. In Panel A, we re-run the baseline results in the positive AQI sensitivity (AQI beta) sub-sample with industry, province, and year fixed effect. In Panel B, we re-run the baseline results in the negative AQI sensitivity (AQI beta) sub-sample with industry, province, and year fixed effect. Detailed definitions of variables are given in Table A1, Appendix A. The *t*-statistics are reported in parentheses. The symbols *, **, and ***indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

innovation investment, the mediator should be significant, and the significance of the independent variable (*A_AQI exposure*) will be reduced after the mediator variable is added to the regression. The indirect or mediating effect is the difference between in column (1) and the direct effect in column (3), the significance of which is checked by the Sobel (1982) test, which is essentially based on *z*-statistics. We use a Sobel (1982) test to examine whether the mediation effect is statistically significant.

Frijns et al. (2013) demonstrate that uncertainty leads to cash flow fluctuations, increasing operational risk and subsequently reducing R&D expenditure. This suggests that operational risk can influence a firm's decision to delay investment, providing a significant economic channel that supports the real options theory in explaining the relationship between corporate innovation investment and adjusted air pollution exposure.

Panel A of Table 12 shows the test results for the mediation effect of net operating cash flow (*CF*). In column (1), the coefficient of *A_AQI exposure* is −0.242, which is the total effect, significant at the 1% level, implying that the adjusted air pollution exposure has a significant negative impact on corporate innovation investment. In column (2), the regression coefficient of *A_AQI exposure* is significantly negative (−0.006), indicating that adjusted air pollution exposure significantly impacts the mediating variable of corporate net operating cash flow. In column (3), the regression coefficient of the independent variable *A_AQI exposure* is −0.228 (the direct effect), still significant at the 1% level, and that of the mediating variable, *CF*, is 2.109 and significant at the 1% level. The indirect or mediating effect[19] is, then, −0.014 (−0.242 + 0.228 or −0.006 × 2.109). Using a Sobel test, we find this mediation effect is significant with $p < 0.01$. In other words, net operating cash flow mediates around 5.2% of the total effect,[20] showing it as an important channel through which adjusted air pollution exposure affects corporate innovation investment.

Previous research indicates that uncertainty exacerbates firms' financial distress. For instance, Francis et al. (2014) find that firms with greater idiosyncratic political exposure face higher costs of bank loans because of the strong positive correlation between uncertainty and information asymmetry. Bordo et al. (2016) demonstrate that as uncertainty rises, bank lending drastically decreases, which could lead to a decrease in corporate innovation investment. We argue that financial distress also heightens the value of waiting, which could potentially be a key economic channel through which the real options theory explains the connection between adjusted air pollution exposure and corporate innovation investment.

Panel B of Table 12 shows the test results for the mediating effect of debt financing cost ($Fincost$). Following Xiang and Li (2022), corporate debt financing cost is calculated as the interest expense for the year divided by its average short- and long-term debt during the year. In column (1), the total effect measured by the coefficient of *A_AQI exposure* is -0.442 with statistical significance at the 1% level, implying that adjusted air pollution exposure adversely affects corporate innovation investment. In column (2), the regression coefficient of *A_AQI exposure* is positive (0.071) and significantly at the 1% level, which means that adjusted air pollution exposure has a significantly positive impact on the mediating variable, $Fincost$. In column (3), while *A_AQI exposure*, direct effect, is negative and still significant at the 1% level with a value of -0.425, the coefficient estimation of the mediating variable, $Fincost$, is -0241 and significant at the 1% level. The indirect or mediating effect is, then, -0.017 ($-0.442 + 0.425$ or 0.071×-0.241). Using a Sobel test, we find this mediation effect is significant with $p < 0.01$. In other words, 3.9% of the total effect is mediated by the debt financing cost, supporting that debt financing cost is an important channel through which adjusted air pollution exposure affects corporate innovation investment.

4.5.2 | Human capital effect

In this section,[21] we examine the role of human capital in this relationship using firms' R&D personnel ratio as a proxy for their reliance on human capital in innovation activities. The productivity and proportion of R&D staff in R&D-intensive firms is a critical factor that draws significant attention of managers and investors. Deteriorating air quality could affect firm innovation as it leads to health issues among key talents, such as increased absenteeism, reduced focus, and even turnover (Bakian et al., 2015; Luo et al., 2022), and this effect will be stronger in firms with more R&D personnel. This low efficiency and productivity of human capital could therefore decrease firm innovation inputs and outputs, especially for the R&D intensive firms.

We divide the full sample into two groups based on the firms' R&D personnel ratio, categorizing them as either above or below the median level. The sub-sample regression results are presented in Table 13, we find that the negative impact of adjusted air pollution exposure on R&D inputs and outputs is more pronounced for R&D intensive firms with a higher R&D personnel ratio. The findings support our conjecture that firms with high adjusted air pollution exposure face challenges such as increased absenteeism and reduced efficiency among R&D personnel, which ultimately hinders innovation input and output.

4.5.3 | Moderating effects

To explore the factors that can mitigate the negative relationship between adjusted air pollution exposure and corporate innovation investment, we introduce the interaction term of corporate ownership type with adjusted air pollution exposure. We use the state-owned enterprises (SOE) dummy and interact it with adjusted air pollution exposure. Compared with non-state-owned enterprises, state-owned enterprises have easier access to loans (Dewenter & Malatesta, 2001) to support long-term and risky innovation investment, being in a better position in

TABLE 12 Mediating effect of net operating cash flow and financing cost.

Panel A: Net operating cash flow (CF) Variables	R&D_Assets	CF	R&D_Assets	Panel B: Financing cost (Fincost) R&D_Assets	Fincost	R&D_Assets
Model	**(1)**	**(2)**	**(3)**	**(1)**	**(2)**	**(3)**
A_AQI exposure	−0.242**	−0.006*	−0.228**	−0.442***	0.071***	−0.425***
	(−2.45)	(−1.98)	(−2.28)	(−3.71)	(4.50)	(−3.63)
CF			2.109***			
			(3.35)			
Fincost						−0.241***
						(−3.57)
Constant	2.193***	−0.124***	2.392***	4.488***	−0.149**	4.452***
	(2.71)	(−5.13)	(3.23)	(8.74)	(−2.20)	(8.68)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Industry	Yes	Yes	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes	Yes	Yes
Province	Yes	Yes	Yes	Yes	Yes	Yes
S.E. Clustering	Firm	Firm	Firm	Firm	Firm	Firm
N	16,952	16,952	16,952	13,037	13,037	13,037
Adj R^2	0.283	0.286	0.286	0.134	0.252	0.135

Panel C: Indirect, Direct, and Total Effects of CF and Fincost			Panel D: Indirect, Direct, and Total Effects of Fincost	
Type	**Effect**	**Estimate**		**Estimate**
Total	A_AQI exposure → R&D_Assets	−0.242	A_AQI exposure → R&D_Assets	−0.442
Direct	A_AQI exposure → R&D_Assets	−0.228	A_AQI exposure → R&D_Assets	−0.425
Indirect	A_AQI exposure → CF → R&D_Assets	−0.014		
Indirect			A_AQI exposure → Fincost → R&D_Assets	−0.017
Sobel test—*Z*- stat		−3.634*** (0.008)		−2.824*** (0.006)
Proportion of total effect that is mediated:		0.052		0.039

Note: This table reports the mediating effects of net operating cash flows (*CF*) and financing cost (*Fincost*) in Panel A and Panel B, respectively. Column (1) shows the regression results of *A_AQI exposure* on *R&D_Assets*. Column (2) of Panel A shows the effect of adjusted air pollution exposure (*A_AQI exposure*) on *CF* and *Fincost* in Panel A and B, respectively. Column (3) shows the effect of *A_AQI exposure* and *CF* and *Fincost* on *R&D_Assets* in Panel A and B, respectively. Panel C presents the indirect, direct, and total effects of *CF* and *Fincost*. Detailed definitions of variables are given in Table A1, Appendix A. The *t*-statistics are reported in parentheses. The symbol *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

innovation than non-state-owned enterprises. The regression results are reported in Table 14. We find that the regression coefficients of the interaction term of SOE and adjusted air pollution exposure, *A_AQI exposure* × *SOE*, are 0.456 and 0.584 in columns (1) and (2), respectively, with statistical significance at least at the 10% level, while

TABLE 13 Human capital effect.

Variables	R&D_Assets (1) R&D Intensive firms	R&D_Assets (2) R&D Light firms	*Inv_PAT_APP*$_{t+1}$ (3) R&D Intensive firms	*Inv_PAT_APP*$_{t+1}$ (4) R&D Light firms
A_AQI exposure	−0.412***	−0.007	−0.161**	−0.024
	(−2.68)	(−0.07)	(−2.09)	(−0.35)
GDP growth	5.904***	3.676***	1.308*	1.999***
	(3.85)	(3.68)	(1.78)	(2.93)
GDP per capita	−2.865***	−2.407***	0.408	−0.154
	(−3.05)	(−3.63)	(0.88)	(−0.32)
Constant	−0.690	1.613***	−4.969***	−4.265***
	(−0.92)	(3.56)	(−12.51)	(−13.13)
Controls	Yes	Yes	Yes	Yes
Industry	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes
Province	Yes	Yes	Yes	Yes
S.E. Clustering	Firm	Firm	Firm	Firm
N	8236	8073	6465	6782
Adj R^2	0.233	0.218	0.215	0.185

Note: This table reports the results of human capital effect on our baseline results. We divide the full sample into two groups based on the firms' R&D personnel ratio, categorizing them as either above or below the median level. The dependent variables are *R&D_Assets* and *Inv_PAT_APP*$_{t+1}$, measured by R&D expenditure to total assets of each firm in *year*$_t$ and the natural logarithm of invention patent applications plus one in *year*$_{t+1}$. The main independent variable is adjusted air pollution exposure (*A_AQI exposure*). Detailed definitions of variables are given in Table A1, Appendix A. The *t*-statistics are reported in parentheses. The symbol *, ** and ***indicate statistical significance at the 10%, 5% and 1% level, respectively.

the coefficients of *A_AQI exposure* are still statistically significant. This indicates that state ownership can mitigate the negative impact of adjusted air pollution exposure on firm innovation investment.

4.6 | Heterogeneity tests

Our findings thus far support the hypothesis that adjusted air pollution exposure negatively impacts corporate innovation investment. However, different internal and external characteristics may generate different results of this impact. To this end, we explore three internal factors: (a) environmental disclosures, (b) managers' risk tolerance, and (c) firm characteristics, such as polluter vs. non-polluter.

First, according to Solikhah and Maulina (2021), environmental disclosures represent a form of corporate responsibility to society by informing people about any negative environmental impact resulting from firm operations. Lin et al. (2021) find that the enterprises have poorer environmental governance and are more indifferent to environmental issues in more polluting areas, resulting in lower-quality or no environmental information disclosures. We expect that our baseline result will be more prominent in firms with environmental information disclosure because these firms pay more attention to environmental issues and are thus more susceptible to the effects of air pollution. Second, the prevailing perception in academic research is that CEO personal risk preferences tend to affect firm risk and performance by implementing different policies (Lewellen, 2006; Schooley & Worden, 1996). Cen and

TABLE 14 Moderating effects.

Variables Model	*R&D_Assets* (1)	$R\&D\_Assets_{t+1}$ (2)
A_AQI exposure	−0.281***	−0.198**
	(2.79)	(−1.96)
A_AQI exposure × *SOE*	0.456*	0.584**
	(1.70)	(1.98)
SOE	0.054	0.070
	(1.07)	(1.22)
Constant	1.969***	1.957***
	(4.35)	(3.76)
Controls	Yes	Yes
Industry	Yes	Yes
Year	Yes	Yes
Province	Yes	Yes
S.E. Clustering	Firm	Firm
N	16,952	13,048
Adj R^2	0.275	0.260

Note: This table reports the results of moderating effects of firm's ownership control. The dependent variables are *R&D_Assets* and $R\&D\_Assets_{t+1}$, measured by R&D expenditure to total assets of each firm and then multiplied by 100 in $year_t$ and $year_{t+1}$. The main independent variable is adjusted air pollution exposure (*A_AQI exposure*). The interacted variable is SOE that takes value of 1 if the firm is state-owned-enterprise (SOE), and 0 otherwise. Detailed definitions of variables are given in Table A1, Appendix A. The *t*-statistics are reported in parentheses. The symbol *, ** and ***indicate statistical significance at the 10%, 5% and 1% level, respectively.

Doukas (2017) find that risk-taking CEOs pursue risky financial and investment policies. Caliendo et al. (2024) find that risk-aversion managers are sensitive to the investment risk associated with training, avoiding more costly training or targeting those with less occupational expertise or nearing retirement. In light of this, we expect managers with low-risk tolerance to be more easily impacted by the firm's uncertainty and make conservative investment decisions. Third, data in Table 2 shows that firms in less polluted industries have higher air pollution exposures. This means that non-polluters are more sensitive to air pollution levels. In light of the above discussion, we expect that the impact of adjusted air pollution exposure on corporate innovation investment is more salient for firms with environmental disclosures, low managers' risk tolerance, and firms belonging to a non-polluted industry.

To investigate these three internal factors, we divide the full sample into two groups by checking whether information on the environment is disclosed in the listed firms' annual reports. We also divide sample firms into two groups based on the manager's risk tolerance, measured above or below the median level of the firm's illiquid assets to total assets. Finally, following the Ministry of Environment and Ecology classifications, we divide the sample firms into polluters and non-polluters. The sub-sample regression results are reported in columns (1), (3), and (5) in Panel A of Table 15 showing that the estimated coefficients of *A_AQI exposure* are negatively and significantly at the 1% levels for firms with environmental information disclosures, low manager's risk tolerance, and non-polluter firms as expected.[22] Furthermore, the *Chow*-tests indicate that the coefficients differ significantly across different sub-samples.

We also consider three external factors: (a) well-developed vs. developing provinces, (b) less-polluted vs. more-polluted provinces, and (c) before and after the 2015 Paris Agreement. First, Bao and Liu (2022) find that environmental attention in developed provinces, such as southern regions, is higher than in the northern regions.

TABLE 15 Heterogeneity tests.

Panel A: Internal factors

Variables	R&D_Assets (1) Environmental disclosure	R&D_Assets (2) Non-environmental disclosure	R&D_Assets (3) Low manager's risk tolerance	R&D_Assets (4) High manager's risk tolerance	R&D_Assets (5) Non-polluter firms	R&D_Assets (6) Polluter firms
A_AQI exposure	−0.286***	0.320	−0.231**	−0.096	−0.346***	0.323
	(−2.75)	(1.17)	(−2.17)	(−0.71)	(−3.65)	(1.58)
GDP growth	3.574***	7.435***	4.978	2.903**	5.005	2.257
	(3.63)	(3.93)	(1.35)	(2.55)	(1.68)	(1.21)
GDP per capita	−2.484***	−3.256***	−3.314***	−1.924***	−3.696***	−0.874
	(−4.08)	(−3.42)	(−6.92)	(−2.69)	(−7.27)	(−0.95)
Constant	0.955**	−3.128*	1.324	1.618***	0.746*	2.491***
	(2.08)	(1.74)	(1.63)	(3.05)	(1.77)	(3.83)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Industry	Yes	Yes	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes	Yes	Yes
Province	Yes	Yes	Yes	Yes	Yes	Yes
S.E. Clustering	Firm	Firm	Firm	Firm	Firm	Firm
N	14,805	1506	8476	8476	11,913	5.039
Adj R^2	0.089	0.143	0.245	0.289	0.284	0.206
Chow-test	0.018**		0.003***		0.026**	

Panel B: External factors

	Well-developed provinces	Developing provinces	Less-polluted provinces	More-polluted provinces	After 2015	Before 2015 (including 2015)
A_AQI exposure	−0.199**	−0.286	−0.346**	−0.031	−0.914***	−0.005
	(−1.94)	(−1.20)	(−2.08)	(−0.27)	(−3.11)	(−0.01)
GDP growth	1.398	5.979***	1.168	4.795***	0.482	−6.065
	(1.14)	(3.28)	(0.76)	(3.45)	(0.82)	(−1.09)
GDP per capita	−2.345***	−2.609*	−3.697***	−1.915*	0.015	3.493
	(−3.25)	(−1.85)	(−4.53)	(−1.76)	(0.07)	(0.56)
Constant	1.294***	1.212	3.343***	0.218	13.269***	21.048***
	(2.69)	(1.44)	(5.40)	(0.38)	(5.38)	(4.48)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Industry	Yes	Yes	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes	Yes	Yes

(Continues)

TABLE 15 (Continued)

Panel B: External factors	Well-developed provinces	Developing provinces	Less-polluted provinces	More-polluted provinces	After 2015	Before 2015 (including 2015)
Province	Yes	Yes	Yes	Yes	Yes	Yes
S.E. Clustering	Firm	Firm	Firm	Firm	Firm	Firm
N	12,907	4045	8476	8476	12,891	2399
Adj R^2	0.263	0.318	0.269	0.287	0.890	0.873
Chow-test	0.052*		0.026**		0.028**	

Note: This table reports the results of heterogeneity tests. To examine the impact of adjusted air pollution exposure and corporate innovation investment, we explore three internal factors: (a) environmental disclosure; (b) manager's risk tolerance, measured by the firm's illiquidity assets to total assets; (c) firms' characteristics: polluter or non-polluter; and two external factors: (d) well-developed provinces and others, we measure the development degree of the provinces using the Fan-Gang index; (e) the firms' headquarter air pollution level, we divide the sample into more polluted and less polluted provinces based on the firms' headquarters' AQI median level; (f) 2015 Paris Agreement. The *t*-statistics are reported in parentheses. The symbol *, ** and *** indicate statistical significance at the 10%, 5% and 1% level, respectively.

The governments in southern regions pay more attention to environmental issues and deal with air pollution issues positively. Similarly, Huang et al. (2022) find that improving government environmental attention inhibits ambient pollution through green development and industrial upgrading. However, this phenomenon is generally more pronounced in developed provinces. Furthermore, due to the Qinling-Huai River policy,[23] the average air quality in southern provinces is better than in northern provinces. Therefore, we expect a more pronounced negative effect for firms in well-developed and less polluted provinces. Second, the Paris Agreement is a climate change agreement signed by 196 countries worldwide and is a unified arrangement for global action to address climate change after 2020. The Paris Agreement was formally put into effect on November 4, 2016, after being approved at the Paris Climate Conference on December 12, 2015, and signed at the United Nations building in New York, USA, on April 22, 2016. On 3 September 2016, the Standing Committee of the National People's Congress (NPC) approved China's accession to the Paris Climate Change Agreement, becoming one of the parties that completed ratification of the agreement.[24] Since then, several carbon policies and pollution protection regulations have been created (Dai & Zhang, 2023; Su et al., 2020). Concerns and awareness about air pollution are given higher priority by both the central government and municipal governments. Thus, a natural question arises whether our baseline results are more pronounced after the 2015 Paris Agreement was signed.

To investigate these three external factors, first, we divide sample firms into developed and developing provinces based on the Fan-Gang marketization index; second, we divide sample firms into more polluted and less polluted provinces based on the median level of the AQI of the firms' headquarters' locations; third, we divide firms into two subsamples: "Before 2015 (including 2015)" and "After 2015." Results reported in columns (1) and (3) in Panel B of Table 15 show that the estimated coefficients of *A_AQI exposure* are negative and highly significant for the firms located in well-developed, less polluted provinces, as expected. For the "After 2015" subsample, column (5) in Panel B shows the coefficient estimate of *A_AQI exposure* is −0.914 with a statistical significance level of 1%. Furthermore, the *Chow*-tests also show that the coefficients differ significantly across different sub-samples. The finding is consistent with our conjectures.

5 | CONCLUSION

This paper creates a novel measure of air pollution exposure by combining the city-level AQI and the firm-level exposure to air pollution, and examines the impact of adjusted air pollution exposure on corporate innovation investment in China. This new measure captures the firms' exposures to abnormal air pollution as perceived by the investors but does not bypass the importance of the inherent negative externality associated with air pollution as an economic 'bad'. We focus on corporate innovation investment because it is unlike traditional investments in tangible assets like capital expenditures, and innovation represents long-term, intangible assets intended to generate future profits. Besides this, innovation requires a longer time horizon and carries higher tail risk. The option to wait is particularly significant for investments in research and development (R&D), given that innovation involves exploring unknown approaches and untested methods (Ferreira et al., 2014), requiring substantial investment in intangible assets.

We find that adjusted air pollution exposure has a negative impact on corporate innovation investment. The results still hold after addressing endogeneity issues and applying a series of robustness checks and endogeneity tests. More importantly, our mediation analysis results suggest that a firm's operational risk and financial distress are critical mediating factors of this impact. We find that adjusted air pollution exposure lowers firms' corporate innovation investment due to reduced corporate net operating cash flow and increased debt financing cost. Our results favor the real options theory which argues that if the investment is irreversible, the uncertainty increases the value of the option to wait, and firms can avoid sunk costs by deferring risky investment projects (Bulan, 2005; Gulen & Ion, 2016). Additionally, we also find that firms with high adjusted air pollution exposure face challenges such as increased absenteeism and reduced efficiency among R&D personnel, which ultimately hinders both innovation input and output. Our results also indicate that state ownership can mitigate the negative impact of adjusted air pollution exposure on innovation investment. Furthermore, the adverse effects of adjusted air pollution exposure are more pronounced for firms with environmental disclosure, low managerial risk tolerance, non-polluting firms, and those located in developed and less polluted provinces. We also observe a significant negative effect of air pollution on firm innovation investment following the 2015 Paris Climate Agreement. Finally, in additional tests examining the differential effects of adjusted air pollution exposure on general technological innovation versus green innovation, we find that firms with high exposure may shift their focus toward environmentally adaptive technologies, likely in response to regulatory or reputational risks.

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ENDNOTES

[1] Numerous scholarly studies find that ambient air pollution may have adverse impacts on human health, such as raising mortality rates from cardiac and respiratory diseases (Franklin et al., 2015), raises suicidal tendencies (Bakian et al., 2015), reduces happiness (Zhang et al., 2017), and leads to anxiety and frustration (Evans et al., 1988), among other problems.

[2] More details about the air pollution anomaly construction are described in Section 3.2.2.

[3] Please see Table 1 and Figure 4.

[4] Nagar et al. (2019) also use the interaction term that multiplies the EPU index by EPU beta to see the interaction effect on investor information asymmetry and management disclosures.

[5] China Banking Regulatory Commission (CBRC), 2014b, No. 40 Document General Office of the China Banking Regulatory Commission, Options on Green Credit Implementation. Available at: http://www.cbrc.gov.cn/EngdocView.do?docID=C5AE0DDAFB3E43DF85DC12DD6840244A.

[6] We sincerely thank the anonymous reviewer for their valuable suggestions, which have strengthened the contribution of our proposed metric.

[7] These six pollutants include sulfur dioxide (SO_2), nitrogen dioxide (NO_2), particulate matter smaller than 10 μm (PM_{10}), particulate matter smaller than 2.5 μm ($PM_{2.5}$), carbon monoxide (CO), and ozone (O_3).

[8] Recent literature introduces a new measure for firm-level climate change exposure based on transcripts of quarterly earnings conference calls (Sautner et al., 2023). However, these measures may be limited by salience bias, where managers overweight the probability of events based on their proximity or ease of recall (Alok et al., 2020). This bias has been observed in managerial overreactions to local disasters, such as increased cash holdings following hurricanes (Dessaint & Matray, 2017) and professional money managers underweighting nearby firms' stocks (Alok et al., 2020). However, we believe our measure does not suffer from this shortcoming.

[9] The Ministry of Environmental Protection of China (MEPC) distinguishes among six categories of AQI: I-excellent (AQI ≤50), II-good (50 < AQI ≤100), III- lightly polluted (100 < AQI ≤150), IV-moderately polluted (150 < AQI ≤200), V-heavily polluted (200 < AQI ≤300) and VI-severely polluted (AQI > 300).

[10] We run the Fama–French three-factor model, Equation (1) for all firms for the whole sample and the sample period to gauge the statistical significance of the overall AQI exposure. The regression results reported in Table A3 show that the coefficient estimate of AQI anomaly is positive and statistically significant at the 1% level, implying that the investor perceives the AQI anomaly as a significant factor. The result is also economically significant: one standard deviation change in abnormal air pollution implies a change equal to 7.57% of excess return.

[11] Furthermore, as shown in Table A3, the correlation between AQI and AQI exposure is −0.053, consistent with the patterns illustrated in Figures 3 and 4. This negative correlation indicates that higher levels of air pollution are associated with lower AQI exposure. Additionally, the weak magnitude of this correlation implies that changes in AQI do not directly or proportionally translate into changes in AQI exposure. This observation aligns with the definition and the calculation of AQI exposure, which reflects investors' perceptions and may be influenced by factors beyond AQI levels alone. The correlation between AQI and adjusted AQI exposure is 0.118, while the correlation between AQI exposure and adjusted AQI exposure is 0.959. These results are consistent with the computational relationship, as adjusted AQI exposure is derived by multiplying AQI and AQI exposure. Together, these findings highlight the distinct characteristics of AQI, AQI exposure, and adjusted AQI exposure, as well as their interdependencies.

[12] Nagar et al. (2019) also use the interaction term that multiplying the EPU index by EPU beta to see the interaction effect on investor information asymmetry and management disclosures.

[13] We thank the anonymous reviewer for suggesting this test and shock.

[14] More details can be found at: https://www.gov.cn/zhengce/content/2018-07/03/content_5303158.htm.

[15] More details can be found at: https://www.gov.cn/zhengce/content/202312/content_6919000.htm.

[16] Here, we also use the mean of exposure of industry *j* over the sample period, $\left|\overline{\beta_{j,y}^{aqi}}\right|$ as alternative measure, the results still exist.

[17] In addition, Tan and Yan (2021) find that air pollution negatively impacts general innovation by exacerbating firms' financial constraints and depleting human capital resources. Wang et al. (2021) find that firms headquartered in a city with severe air pollution tend to engage less in innovation activities, as air pollution drives the migration of highly skilled employees. However, Ma and He (2023) find that firms in polluted areas are more likely to engage in green innovation as a strategic response to regulatory pressures and societal expectations. Thus, air pollution exposure tends to have a dual effect: it may hamper general innovation by reducing productivity and increasing operational costs while simultaneously encouraging green innovation due to regulatory incentives and stakeholder pressures. We conduct additional tests to examine the differential effects of adjusted air pollution exposure on general technological innovation and green innovation. The results, as shown in columns (1) and (2) in Table A6, indicate that adjusted air pollution exposure negatively affects the application of general technological patents. However, for green innovation, the impact is positive, as shown in column (3), or insignificant, as observed in column (4) when AQI and AQI exposure variables are included in the analysis. These findings suggest that firms with high adjusted air pollution exposure may shift their focus toward environmentally adaptive technologies to address regulatory or reputational risks. We thank the anonymous reviewer for suggesting this study.

[18] The effect is more pronounced for firms with positive AQI sensitivity. We thank an anonymous reviewer for spotting this interesting and valuable result. We believe this asymmetry may stem from two primary factors. First, as previously discussed, firms with positive AQI sensitivity tend to be concentrated in pollution-intensive industries. These firms are more likely to encounter tighter liquidity constraints, reflected in reduced operating performance and more limited access to low-cost financing. Second, firms in these sectors may be more vulnerable to declines in human capital efficiency, as adverse environmental conditions can negatively affect the productivity and well-being of R&D personnel. These findings are also consistent with the results of our mediation analysis. Together, these financial and operational frictions offer a plausible explanation for why the adverse effects of air pollution exposure on innovation are more pronounced among firms with positive AQI sensitivity.

[19] Because decimal places for coefficients are preserved, the number gained by these two approaches should be equivalent or extremely similar.

[20] The number is produced by Sobel test or can be calculated by mediating effect/total effect. More details about Soble test, please see https://www.trentonmize.com/software/sgmediation2.

[21] We thank the anonymous reviewer for suggesting this test.

[22] Each regression includes GDP growth and per capita GDP by provinces as additional controls and other firm-level characteristics.

[23] The Huai River (please see Figure 3) splits China into northern and southern parts, and China's central government provides free winter heating only in cities north of the Huai River. Because the centralized winter heating system rests on the use of inefficient coal-based hot water boilers, which leads to substantial energy loss and releases a significant amount of air pollutants. This policy has unintentionally worsened air quality in northern regions, creating a discontinuity in terms of AQI for cities across the two sides of the Huai River (Lepori, 2016; Li et al., 2021).

[24] More details please see: https://unfccc.int/process-and-meetings/the-paris-agreement.

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APPENDIX A

TABLE A1 Variables definition.

	Variables	Definition
Dependent variable	R&D_Assets	The ratio of R&D expenditure to total assets multiply by 100.
	Inv_PAT_APP	Natural logarithm of total number of invention patents applications plus one.
Explanatory variable	A_AQI exposure	Adjusted air pollution exposure, measured by AQI $\times$ AQI exposure.
	AQI	Annual average Air Quality Index (AQI) divide 1000 of the city where firm *i*'s headquarter is located.
	AQI exposure	Air pollution exposure is the absolute air pollution beta, which is calculated through the Fama–French three-factor model.
Control variables	Size	Natural logarithm of total assets.
	Lev	The ratio of total debt to total assets.
	ROA	Returns on assets, calculated as net income over total assets.
	Growth	The growth rate of sales.
	Tobin's Q	The ratio of market value to book value of assets.
	KZ	KZ Index; higher KZ index, higher financial constraints.
	Top1	The shareholding ratio of the top one major shareholder.
	ListAge	The natural logarithm of current year minus listed year and plus one, ln (current year-listed year$+$1).
	BoardSize	The natural logarithm of the number of board members.
	IndepR	The proportion of independent directors.
	Dual	The dummy variable equals 1 if chairman of the board and CEO are the same individual, and 0 if otherwise.
	Mshare	Management's shareholding
	Fixed	The ratio of fixed assets to total assets.
	Big 4	Dummy variable that equals 1 if the firm employs a Big Four auditor, and 0 otherwise
	SOE	The dummy variable equals 1 if the firm is state-owned-enterprise (SOE), and 0 if otherwise.
	Polluter	Dummy variable that equals 1 if firm *i* belongs to the polluting industries, and 0 otherwise. Categorizations of these industries follow the CSRC Listed Company Industry Classification Guidelines (2012).
	CF	The ratio of net operating cash flow to the total assets.
	Fincost	Debt financing cost: Interest expense/Average short- and long-term debt (%).
	Green_Inv_PAT_APP	Natural logarithm of total number of green invention patents applications plus one.
	R&D personnel ratio	The ratio of the number of R&D personnel to the total number of employees in each firm.

Note: This table presents definitions of all the variables.

TABLE A2 Distribution of air pollution by province.

Province	Mean	Median	Min	Max	SD
Hainan	0.043	0.042	0.019	0.103	0.008
Tibet	0.051	0.050	0.038	0.058	0.005
Yunnan	0.052	0.054	0.041	0.060	0.004
Guizhou	0.054	0.051	0.039	0.128	0.012
Fujian	0.054	0.053	0.043	0.082	0.005
Guangdong	0.060	0.057	0.045	0.147	0.011
Guangxi	0.060	0.057	0.047	0.093	0.009
Jiangxi	0.065	0.065	0.048	0.084	0.007
Zhejiang	0.073	0.071	0.047	0.181	0.013
Jilin	0.073	0.070	0.052	0.101	0.013
Chongqing	0.074	0.072	0.062	0.093	0.009
Shanghai	0.074	0.072	0.047	0.125	0.008
Heilongjiang	0.074	0.070	0.051	0.103	0.014
Qinghai	0.080	0.084	0.069	0.090	0.007
Liaoning	0.080	0.078	0.065	0.112	0.012
Hunan	0.080	0.080	0.053	0.172	0.014
Anhui	0.081	0.083	0.045	0.147	0.013
Nei Mongol	0.083	0.083	0.057	0.139	0.015
Sichuan	0.083	0.077	0.053	0.155	0.013
Jiangsu	0.083	0.083	0.046	0.239	0.015
Gansu	0.084	0.087	0.052	0.102	0.013
Ningxia	0.086	0.086	0.076	0.100	0.006
Hubei	0.087	0.086	0.059	0.138	0.013
Shandong	0.092	0.094	0.040	0.144	0.019
Xinjiang	0.094	0.094	0.056	0.124	0.015
Beijing	0.095	0.094	0.061	0.125	0.017
Shanxi	0.096	0.098	0.073	0.123	0.012
Tianjin	0.098	0.099	0.085	0.121	0.010
Shanxi	0.102	0.100	0.060	0.218	0.016
Henan	0.111	0.111	0.072	0.172	0.018
Hebei	0.114	0.109	0.066	0.246	0.029

Note: This table provides the summary statistics for AQI in our sample in each province.

TABLE A3 Correlation matrix.

Variables		1	2	3	4	5	6	7	8	9	10	11
1	R&D_Assets	1.000										
2	A_AQI exposure	−0.044	1.000									
3	AQI	−0.072	0.118	1.000								
4	AQI exposure	0.044	0.959	−0.053	1.000							
5	size	−0.189*	0.048***	0.057***	−0.245***	1.000						
6	roa	0.114***	0.001	0.001	0.140***	−0.020***	1.000					
7	lev	−0.176***	0.026***	0.014*	−0.141***	0.522***	−0.353***	1.000				
8	growth	0.049**	0.066***	−0.005	0.069***	0.041***	0.275***	0.024***	1.000			
9	tobinq	0.267***	0.014**	−0.025***	0.053***	−0.295***	0.205***	−0.281***	0.088***	1.000		
10	KZ	−0.095***	0.075***	−0.025***	−0.179***	0.205***	−0.575***	0.545***	−0.088***	−0.045***	1.000	
11	top1	−0.150***	−0.047***	0.043***	0.030***	0.174***	0.140***	0.038***	−0.025***	−0.083***	−0.121***	1.000
12	board	−0.087***	−0.061***	0.096***	−0.041***	0.261***	0.004	0.131***	−0.013***	−0.099***	0.042***	0.006***
13	indep	0.036***	0.019***	−0.051***	−0.015*	−0.018**	−0.011	−0.013*	−0.010	0.045***	−0.002***	0.055***
14	dual	0.097***	0.045***	−0.107***	0.082***	−0.170***	0.051***	−0.127***	0.035***	0.070***	−0.088***	−0.018***
15	mshare	0.126***	−0.023***	−0.040***	0.178***	−0.358***	0.175***	−0.268***	0.063***	0.016**	−0.245***	−0.069***
16	fixed	−0.223***	−0.068***	0.066***	−0.072***	0.149***	−0.071***	0.127***	−0.069***	−0.104***	0.095***	0.128***
17	big4	−0.009	0.025***	0.022***	−0.034***	0.359***	0.026***	0.120***	−0.006	−0.057***	0.009***	0.138***
18	listage	−0.124***	0.013*	0.034***	−0.475***	0.445***	−0.259***	0.310***	−0.076***	−0.018**	0.359***	−0.108***
19	soe	−0.145***	−0.014*	0.138***	−0.139***	0.383***	−0.083***	0.263***	−0.078***	−0.118***	0.165***	0.242***
20	polluter	−0.111***	−0.026***	0.039***	−0.043***	0.076***	0.053***	−0.040***	−0.020***	−0.053***	−0.048***	0.057***

(continuous) Variables		12	13	14	15	16	17	18	19	20
1	R&D_Assets									
2	A_AQI exposure									
3	AQI									
4	AQI exposure									
5	size									

(Continues)

TABLE A3 (Continued)

(continuous) Variables		12	13	14	15	16	17	18	19	20
6	roa									
7	lev									
8	growth									
9	tobinq									
10	KZ									
11	top1									
12	board	1.000								
13	indep	−0.602	1.000							
14	dual	−0.175***	0.116**	1.000						
15	mshare	−0.187***	0.072***	0.198***	1.000					
16	fixed	0.133***	−0.042***	−0.087***	−0.178***	1.000				
17	big4	0.069	0.043***	−0.055***	−0.134***	0.047***	1.000			
18	listage	0.134***	−0.010***	−0.190***	−0.430	0.159***	0.052***	1.000		
19	soe	0.270***	−0.058***	−0.266***	−0.415***	0.186***	0.157***	0.325***	1.000	
20	polluter	0.077***	−0.055***	−0.028***	−0.055***	0.308***	0.006	0.095***	0.051***	1.000

Note: This table reports the correlation coefficients between key variables. Definitions of variables are in Table A1, Appendix A. The superscripts *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

TABLE A4 Fama–French three factors regression.

Variables	Excess return (ER)
MKT	0.931***
	(117.14)
SMB	1.022***
	(79.07)
HML	−0.305***
	(−20.09)
AQI Anomaly	0.054**
	(2.42)
Constant	0.005***
	(65.51)
Firm	Yes
Year	Yes
Province	Yes
S.E. Clustering	Firm
N	228,969
Adj R^2	0.206

Note: This table reports the sensitivity of AQI anomaly using the Fama–French three-factor model for the whole sample period: $R_{i,t} - r_{f,t} = \alpha + \beta_{i,t}^{mkt} MKT_t + \beta_{i,t}^{smb} SMB_t + \beta_{i,t}^{hml} HML_t + \beta_{i,\ t}^{aqi} AQI\,Anomaly_t + e_t$; where, $R_{i,t}$ is the contemporaneous return on firm i in month t, $r_{f,t}$ is the risk-free rate in month t. MKT_t, SMB_t, and HML_t are three Fama–French factors: the excess market returns, the factors small-minus-big, and the factors high-minus-low in month t, respectively. AQI $Anomaly_t$ is the abnormal AQI for each listed firm defined as the difference between $AQI_{i,t}$ of the firm i's headquarter city on month t and the average of AQI for all cities in the same month. This table provides the result to show the statistical and economic significance of beta estimation using Fama–French three factors rolling regression.

TABLE A5 Baseline results under different sub-samples.

Panel A: Sub-samples based on quantiles of AQI (independent variable AQI exposure)					
	R&D _Assets (1)	*R&D _Assets* (2)	*R&D _Assets* (3)	*R&D _Assets* (4)	*R&D _Assets* (5)
Variables	AQI_1	AQI_2	AQI_3	AQI_4	AQI_5
AQI exposure	−0.004	−0.004	−0.015	−0.016	−0.001
	(−0.12)	(−0.51)	(−1.22)	(−1.15)	(−0.04)
Constant	3.168	3.168***	2.876***	2.281**	2.121**
	(1.00)	(4.14)	(3.76)	(2.09)	(2.14)
Controls	Yes	Yes	Yes	Yes	Yes
Industry	Yes	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes	Yes
Province	Yes	Yes	Yes	Yes	Yes
N	3297	3297	6587	9876	3177
Adj R^2	0.291	0.291	0.277	0.284	0.292

Panel B: Sub-samples based on the median level of AQI and AQI exposures				
	High AQI high exposure	High AQI low exposure	Low AQI low exposure	Low AQI high exposure
Variables	(1)	(2)	(3)	(4)
A_AQI exposure	−0.071	−2.275**	−3.197*	−0.469**
	(−0.49)	(−2.04)	(−1.78)	(−2.29)
Constant	3.407***	0.082	2.892***	3.244***
	(3.30)	(0.10)	(3.10)	(3.35)
Controls	Yes	Yes	Yes	Yes
Industry	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes
Province	Yes	Yes	Yes	Yes
N	3831	4268	3890	4317
Adj R^2	0.302	0.294	0.270	0.287

Note: This table provides the results to show the baseline results of sub-samples based on (1) quantiles of AQI (Panel A), where AQI_1 is the First quantile (low AQI index), and AQI_5 is the Last quantile (high AQI index); and (2) the median level of AQI and AQI exposures (Panel B). In Panels A and B, the main independent variable is AQI exposure and A_AQI exposure, respectively. The *t*-statistics are reported in parentheses. The symbols *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

TABLE A6 Further analysis on green innovation.

Variables	$Inv\_PAT\_APP_{t+1}$ (1)	$Inv\_PAT\_APP_{t+1}$ (2)	$Green\_Inv\_PAT\_APP_{t+1}$ (3)	$Green\_Inv\_PAT\_APP_{t+1}$ (4)
A_AQI exposure	−0.108***	−0.091**	0.177*	−0.194
	(−3.63)	(−2.49)	(1.82)	(−0.70)
AQI		2.415*		2.909**
		(1.89)		(2.08)
AQI exposure		−0.004		0.032
		(−0.59)		(1.28)
Constant	−4.068***	−4.192***	10.717***	10.479***
	(−2.92)	(3.41)	(16.86)	(16.22)
Controls	Yes	Yes	Yes	Yes
Industry	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes
Province	Yes	Yes	Yes	Yes
S.E. Clustering	Firm	Firm	Firm	Firm
N	10,583	10,583	2.512	2512
Adj R^2	0.202	0.203	0.125	0.127

Note: This table provides the results to show the differential effects of adjusted air pollution exposure on general technological innovation and green innovation. The main dependent variables are the natural logarithm of total number of invention patents application plus one in $year_{t+1.}$: $(Inv\_PAT\_APP_{t+1})$ and the natural logarithm of total number of green invention plus one in $year_{t+1}$; $(Green\_Inv\_PAT\_APP_{t+1})$. The main independent variable is adjusted air pollution exposure (*A_AQI exposure*). The *t*-statistics are reported in parentheses. The symbols *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

TABLE A7 Endogeneity test—propensity scores matching analysis.

Variables	No. of observations if adjusted air pollution exposure dummy = 1	Mean if adjusted air pollution exposure dummy = 1	No. of observations if adjusted air pollution exposure dummy = 0	Mean if adjusted air pollution exposure dummy = 0	Mean difference	t-value
Panel A. Pre-matched differences in characteristics between high-adjusted air pollution exposure and low-adjusted air pollution exposure						
Size	8476	21.821	8476	22.307	−0.486***	−26.32
ROA	8476	0.053	8476	0.040	0.013***	11.82
Lev	8476	0.361	8476	0.402	−0.041***	−13.99
Growth	8476	0.209	8476	0.163	0.046***	8.02
Tobin's Q	8476	2.303	8476	2.082	0.221***	10.34
KZ	8476	0.764	8476	1.047	0.283***	11.26
Top1	8476	0.332	8476	0.330	0.002	0.67
Board	8476	2.090	8476	2.105	−0.015***	−4.97
IndepR	8476	0.377	8476	0.379	−0.002**	−2.38
Dual	8476	0.376	8476	0.330	0.046***	6.08
Mshare	8476	0.221	8476	0.164	0.057***	17.67
Intangibility	8476	0.045	8476	0.044	0.001***	3.82
Fixed	8476	0.197	8476	0.195	0.002***	5.58
Big4	8476	0.040	8476	0.060	−0.020***	−5.82
Listage	8476	1.528	8476	2.023	−0.495***	−42.39
SOE	8476	0.147	8476	0.243	−0.096***	−15.48
Polluter	8476	0.252	8476	0.287	−0.035***	−5.05
Panel B. Post-matched differences in characteristics between high-adjusted air pollution exposure and low-adjusted air pollution exposure						
Size	6070	21.821	6070	21.872	−0.051*	−1.96
ROA	6070	0.053	6070	0.057	−0.003	−1.10
Lev	6070	0.361	6070	0.360	0.001	0.25
Growth	6070	0.210	6070	0.218	−0.008	−1.29
Tobin's Q	6070	2.303	6070	2.277	0.026	1.13
KZ	8476	0.764	8476	0.771	0.007	0.81
Top1	6070	0.332	6070	0.331	0.001	0.36
Board	6070	2.090	6070	2.092	−0.002	−0.78
IndepR	6070	0.377	6070	0.376	0.001	1.23
Dual	6070	0.376	6070	0.379	−0.003	−0.39
Mshare	6070	0.221	6070	0.217	0.004	1.32
Intangibility	6070	0.045	6070	0.044	0.001	1.08
Fixed	6070	0.196	6070	0.195	0.001	1.32
Big4	6070	0.040	6070	0.045	−0.004	−1.4
Listage	6070	1.528	6070	1.521	0.008	0.57

TABLE A7 (Continued)

Variables	No. of observations if adjusted air pollution exposure dummy = 1	Mean if adjusted air pollution exposure dummy = 1	No. of observations if adjusted air pollution exposure dummy = 0	Mean if adjusted air pollution exposure dummy = 0	Mean difference	t-value
SOE	6070	0.147	6070	0.150	−0.002	−0.44
Polluter	6070	0.252	6070	0.265	−0.013*	−1.84

Note: Table A7 presents pre-matching and post-matching differences in characteristics between high-adjusted air pollution exposure and low-adjusted air pollution exposure from the propensity score regression. The logit model is used to estimate propensity scores, where the dependent variable is the dummy variable, which equals 1 if the adjusted air pollution exposure for the firm is above the median and 0 otherwise. Definitions of variables are in Table A1, Appendix A. The *t*-statistics are calculated based on robust standard errors. The superscripts *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.