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Impact of Urban Air Quality on Total Factor Productivity: Empirical Insights from Chinese Listed Companies

Xiaowei Ding [1], Panfeng Wang [2], Xuyan Jiang [1,*], Wenyi Zhang [3], Boris I. Sokolov [1] and Yali Liu [4]

1 Department of Credit Theory and Financial Management, St. Petersburg State University, Universitetskaya Nab. 7/9, St. Petersburg 191034, Russia; xiaoweiding06796@gmail.com (X.D.); b.i.sokolov@spbu.ru (B.I.S.)
2 Department of Risk Management and Insurance, St. Petersburg State University, Universitetskaya Nab. 7/9, St. Petersburg 191034, Russia; st091313@student.spbu.ru
3 Department of Industrial Management and Economic Trade, Peter the Great St. Petersburg Polytechnic University, Polytechnicheskaya, 29 B, St. Petersburg 195251, Russia; wenyz0612@gmail.com
4 Department of Statistics, Accounting and Audit, St. Petersburg State University, Universitetskaya Nab. 7/9, St. Petersburg 191034, Russia; 18193158922@163.com
* Correspondence: helen.jiang.90@mail.ru

Abstract: Urban air quality is inextricably linked to the operations of micro-firms. This paper employs the "Qinling-Huaihe" River demarcation as an instrumental variable to construct a regression discontinuity design (RDD) coupled with the two-stage least squares (2SLS) approach. This methodological framework is utilized to investigate the influence of urban air quality on the corporate total factor productivity (CTFP) of publicly listed manufacturing firms from 2015 to 2020. Drawing on the broken windows theory of urban decay and the general equilibrium theory, this research elucidates a significant adverse effect of urban air pollution on CTFP. We rigorously confirm the validity of the RDD by conducting covariate continuity tests and manipulating distributional variables. Furthermore, the robustness of the baseline regression outcomes is substantiated through a series of sensitivity, robustness, and endogeneity checks, employing alternative instrumental variables. The analysis extends to examining the heterogeneity across environmental attributes, regional features, and green branding. The mechanistic investigation reveals that public environmental concerns, financing constraints, and investments in technological innovation serve as mediators in the nexus between urban air pollution and CTFP. Additionally, it is observed that environmental regulation exerts a positive moderating influence, whereas female leadership has a negative impact in this context. The imperative for timely environmental governance is underscored by these findings, which offer crucial insights for policymakers seeking to refine business environment strategies and for corporations aiming to pursue sustainable growth.

Keywords: urban air quality; corporate total factor productivity; impact mechanism; Qinling-Huaihe River line

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1. Introduction

The relentless increase in the global population coupled with continuous advancements in human productivity has led to widespread environmental pollution and ecological damage, which threaten the survival and progress of humanity. Following the initiation of policies aimed at reform and opening up, China has witnessed substantial economic growth, markedly elevating the living standards of its populace. Nonetheless, the economy's immense scale and rapid consumption of energy are exacerbating resource depletion and air pollution issues. The broken window theory suggests that such an approach to development, which prioritizes economic expansion, adversely impacts not only residents' well-being but also the sustainable growth of urban economies. In response, in 2020, China's central government set forth the strategic goals of achieving "carbon peak" and "carbon neutrality" to foster green growth [1]. This initiative lays a solid groundwork for cultivating a symbiotic relationship between environmental management and economic expansion. Businesses are progressively participating in corporate social responsibility efforts, aiming to enhance urban air quality and foster a clean energy environment, which are vital for boosting total factor productivity and facilitating superior quality development.

The stakeholder theory suggests that proactive engagement in corporate social responsibility can significantly mitigate air pollution, with eco-innovation playing a moderating role in this dynamic [2]. Additionally, the growth of the digital economy offers support for the smart development of urban areas, enhancing their economic resilience while simultaneously promoting continuous improvements in air quality [3]. Macro-level policies are crucial in influencing the quality of air. Çitil et al. [4] argue that the quality of institutions and the stability of the political environment are effective in enhancing air quality. The "pollution halo" hypothesis argues that foreign direct investment (FDI) can lead to a reduction in carbon dioxide emissions by driving technological advancements and improving the quality of institutions [5]. However, there is a notable correlation between higher population density and degraded air quality [6]. Furthermore, research shows that poverty, income inequality, and disparities in energy use are associated with increased carbon emissions and larger ecological footprints [7].

Air pollution detrimentally influences the economic progression of society, individual well-being, and corporate growth. From a household finance perspective, it burdens residents with healthcare costs, diminishes labor productivity, and influences income distribution adversely [8]. Implementing strategies to improve air quality is vital for safeguarding public health and reducing economic burdens. Farzanegan et al. [9] highlight that air pollution may cause population movements, utilizing concepts from urban comfort and migration theories. Furthermore, studies indicate that air pollution can incite criminal and unethical behaviors by impacting mental states, drawing from criminal psychology and environmental influences on behavior [10,11]. Additionally, the impact of air pollution on micro-firms has been explored, particularly how they navigate the complex, fluctuating external economic landscape. Investigations into the correlation between air pollution and corporate performance have mainly focused on the adverse effects on financial outcomes, the adoption of green innovations, and environmental metrics [12]. From a risk management standpoint, air pollution undermines firms' risk-taking abilities, thereby affecting their strategic decisions [13]. Furthermore, air pollution also triggers the brain drain, reduces employee productivity and causes stock price volatility [14]. Therefore, tackling air pollution has emerged as one of the foremost challenges confronting economic agents in the market. The most efficient approach to enhancing the quality of urban air is to employ economic and institutional interventions. In addition to the aforementioned measures, environmental levies and eco-friendly financial policies [15], the Clean Air Act [16], vehicle restriction policies [17], and transport network companies have also been employed to address the issue of air pollution. The implementation of shared mobility services [18] and environmental information disclosure policies [19] has significantly reduced the negative externalities of air pollution, improved the well-being of residents, and contributed to the city's sustainable development. Furthermore, the prediction and monitoring of air quality are of great importance. Aram et al. [20] employed both mechanistic and machine-learning models to classify air quality, resulting in enhanced accuracy and the streamlined adoption of preventive and control measures in advance.

In summary, current academic research focuses on identifying factors that influence urban air quality, their economic consequences, and related management strategies. According to the general equilibrium theory, the key to transitioning from rapid to high-quality growth in China is enhancing the overall factor productivity. However, there is a notable gap in understanding how air pollution affects corporate total factor productivity (CTFP). It is also unclear whether the relationship between air pollution and CTFP is moderated by the presence of female leadership and environmental regulations. To address these issues, this study applies the broken window theory of urban decline and the general equilibrium theory to examine the direct impact of air pollution on CTFP, exploring both its heterogeneity and its underlying mechanisms. This research utilizes a regression discontinuity design (RDD) in conjunction with two-stage least squares (2SLS) using panel data of Chinese listed manufacturing firms from 2015 to 2020. The contributions and innovations of this paper can be summarized as follows:

(1) We tackle the endogeneity problem by employing the "Qinling-Huaihe" River line as an instrumental variable. It needs to be emphasized that the "Qinling-Huaihe" River line is the geographical boundary between northern and southern China and the 0 °C isotherm in January. Therefore, the government implements a centralized heating policy for the north in response to the temperature difference between north and south. Li and Zhang [21] pointed out that there is little possibility of human manipulation in the implementation of a differentiated heating policy. Consequently, the "Qinling-Huaihe" River line can be considered an instrumental variable. Subsequently, we use a combination of the 2SLS and RDD methods to investigate the impact mechanism of urban air quality on CTFP.
(2) This study concludes that urban air pollution negatively impacts CTFP. We assessed the effectiveness of the RDD through a continuity test of covariates and a manipulation test of the running variable. Simultaneously, the credibility of the baseline regression results was confirmed by conducting a bandwidth sensitivity test, as well as substituting the independent, dependent, and instrumental variables.
(3) The heterogeneity was also examined across three dimensions: environmental attributes, regional characteristics, and green branding. Our findings suggest that the negative impact of urban air quality on CTFP is more pronounced in subgroup regressions for non-Eastern, highly polluted, and firms with a poor green image.
(4) Mechanism analyses demonstrate that urban air pollution reduces CTFP by increasing public environmental concern, intensifying financing constraints, and hindering investment in technological innovation.
(5) By constructing an interaction term, we find that environmental regulation exerts a negative moderating effect on the relationship between urban air quality and CTFP, while female ownership exhibits a positive moderating effect.

Section 2 provides a thorough theoretical examination and develops hypotheses concerning the impact of air pollution on CTFP and its transmission mechanisms. Section 3 details the materials and methods utilized in this study. Section 4 discloses the results obtained from the research. Section 5 includes a comprehensive discussion of the findings, while Section 6 concludes by analyzing the implications and limitations of this study and offering recommendations for future research endeavors.

2. Theoretical Analysis and Hypothesis Formulation

2.1. Air Pollution and CTFP

Businesses, as critical entities in the market economy, bear both responsibility for and the consequences of air pollution. To enhance the total factor productivity and foster high-quality development, they need to find an equilibrium between environmental impact and business efficiency. A substantial body of research has established a negative relationship between air pollution and business performance. Specifically, haze has been shown to adversely affect CTFP, significantly disrupting business activities [22]. In the Yangtze River Delta (YRD), China's most economically vibrant region, air pollution is also a key factor affecting manufacturing productivity. Cao et al. [23] identified a significant negative effect of air pollution on manufacturing productivity, more so in colder climates. Additionally, air pollution's impact is not confined to its immediate area; it has spatial spillover effects. Le et al. [24] argued that air quality improvements benefit not only local firms' productivity but also positively influence adjacent areas, a finding corroborated by Liu et al. [25].

Employees, as essential assets of companies, significantly influence CTFP. When viewed through the lens of human capital, investing in air pollution control is deemed a vital investment in workforce capital [26]. From a cognitive productivity standpoint, air pollution detrimentally impacts employees' physical and mental health, thus affecting their efficiency and overall well-being. Given the mobility of skilled workers, they might seek employment in less-polluted areas, prompting firms in polluted regions to enhance their benefits to retain talent, which could elevate administrative costs. Moreover, if pollution-related compensations do not align with employees' expectations, it could lead to a talent exodus, adversely impacting firm productivity [27]. On the investment and financing front, investors tend to be cautious about backing firms in high-pollution areas to mitigate investment risks [28], leading to more challenging financing conditions for these firms and negatively influencing their productivity. In essence, air pollution can engender a detrimental cycle impeding corporate progress: the worse the urban air quality, the lower the CTFP. Thus, we propose the following hypothesis.

H1. *Air pollution inhibits CTFP.*

2.2. Mediating Effects of Public Environmental Concerns, Financing Constraint Intensity and Technological Innovation Investment

China's economic growth has not only fulfilled the material and cultural needs of its people but also played a significant role in enhancing their environmental education. This advancement has heightened citizens' awareness of their ecological surroundings, encouraging the adoption of green consumption behaviors and the assumption of ecological responsibilities [12]. As a result, environmental consciousness has deepened among the populace, with sustainability and low-carbon practices emerging as the main strategies in their production and lifestyle choices. In their study, Canha et al. [29] explored how Portuguese citizens perceive air quality and found notable differences in levels of concern about urban air quality across various demographic groups, particularly among urban industrial populations impacted by pollution, who exhibit heightened environmental concerns. Additionally, the theory of the information transfer effect posits that improved disclosure of urban air quality information can boost public environmental awareness. With more accessible air quality data, the public's comprehension of and engagement with environmental issues are likely to enhance [30].

The "cumulative effect" and "spillover effect" attributes of air pollution progressively and markedly diminish residents' sense of well-being [31]. The expansion of mass media has broadened avenues for public engagement in environmental conservation and has amplified its role in oversight. Yang et al. [32] employed the Baidu index to gauge public environmental concern in China, revealing that escalating air pollution intensifies public anxiety about the environment. Similarly, Du et al. [33] investigated how growing public environmental consciousness affects corporations. They found that heightened public environmental concern poses challenges for high-pollution companies attempting to penetrate regional markets, compelling them to augment their environmental investments and curtail emissions. Furthermore, an uptick in public environmental awareness, induced by air pollution, encourages green investors to adopt more environmentally responsible practices and preferences, thus spurring on the demand for green financial instruments like green bonds [34]. In essence, this paper posits that air pollution's impact on CTFP is mediated by public environmental concern, leading to the formulation of the following hypothesis.

H2(a). *Air pollution leads to increased public environmental concern, thereby inhibiting CTFP.*

The detrimental effects of air pollution significantly influence corporate investment and financing decisions. Numerous studies have demonstrated that air pollution profoundly impacts the extent of the financial constraints faced by businesses. Through a cost management lens, Farooq et al. [28] applied a Generalized Method of Moments (GMM) model to assess how air pollution affects the investment behaviors of non-financial firms in BRICS countries. They found that increased air pollution leads to heightened compliance costs, which in turn impose financial restrictions on investment endeavors, thereby limiting firms' capacity for risk-taking. Zhang et al. [35] observed that air pollution aggravates firms' information environment and financial constraints due to information asymmetry, resulting in significant underpricing during initial public offerings (IPOs). On the other hand, considering green finance and governmental intervention in environmental preservation, Shen et al. [36] presented a contrasting perspective. They argued that acute air pollution exerts considerable environmental pressure on governments, prompting them to ease green financing thresholds for companies via green credit policies, thus aiding their ecological transition. Conclusively, we align with the view of Viet et al. [37] that the intense financial restrictions engendered by air pollution obstruct the improvement of productivity investments, subsequently diminishing CTFP. Therefore, we propose the following hypothesis.

H2(b). *Air pollution leads to an increase in the financing constraint intensity, thereby restraining CTFP.*

Technological innovation is a crucial strategy for firms aiming to boost their overall productivity. With the escalation of air pollution, corporations encounter strict environmental regulations, necessitating substantial allocations toward environmental compliance and pollution mitigation efforts to protect stakeholder interests. Through the lens of the resource-based view, air pollution increases the regulatory and social responsibility costs for companies, which in turn leads to a crowding-out effect on investments in technological innovation. Such innovation is characterized by extended development periods, significant costs, and high risks. Investors, influenced by the deteriorating air quality, may develop a negative outlook on the potential success of projects, thereby restraining investments in technological advancements. Utilizing human capital theory, Tan and Yan [38] argued that cities with higher levels of air pollution become less attractive to skilled and educated workers from outside and may experience a brain drain internally. Additionally, considering pollution's spillover effects, air pollution curtails firms' technology development endeavors by escalating human capital and labor expenses. It also adversely affects technological innovation in neighboring areas due to its diffusion [39]. Consequently, we posit that air pollution creates a "capital crowding-out effect" and a "human resource drain effect" on technological innovation, subsequently impeding CTFP enhancement. Thus, a hypothesis is formulated accordingly.

H2(c). *Air pollution inhibits CTFP by reducing technological innovation investment.*

2.3. Moderating Effects of Environmental Regulation and Female Management

Current theoretical frameworks concerning the economic effects of environmental regulation include the ecological Kuznets curve, the Porter hypothesis, and the pollution haven hypothesis. Analyzing global data, Chen et al. [40] found that the ecological Kuznets curve and the pollution haven hypothesis hold for countries with low institutional quality, while the pollution halo effect is observed in nations undergoing a green transition. In contrast, based on the compliance cost hypothesis, Lee and Lee [41] reached a different conclusion. Using a dynamic panel data model and a multi-level linear model with data from Korean listed companies, they demonstrated that environmental regulations lead firms to increase environmental investments, elevating production costs, reducing product profit margins, and hindering corporate evolution and progress. Thus, they determined that the Porter effect does not apply to South Korea. Similarly, Wang et al. [42] argued that while environmental regulation can curb pollution to some extent, its punitive nature increases production costs, adversely affecting technological innovation and significantly restraining CTFP. Stringent environmental regulations force companies to allocate more resources to pollution control, crowding out investments in productivity, which is not conducive to enhancing CTFP. China is shifting from prioritizing economic growth regardless of the environmental consequences to a green development paradigm focused on sustainability and harmony with nature [43]. Yet, the transition is progressing slowly, with only a rudimentary green finance system, including environmental taxes and green credits, established by the central and local governments. A comprehensive environmental governance framework that aligns with ecological regulations is still lacking. Enhancing the quality of governmental regulation, strengthening legal adherence, combating corruption, and improving governance are imperative. Therefore, we propose the following hypothesis.

H3(a). *Environmental regulation promotes the relationship between air pollution and CTFP.*

The feminist ethic of care theory posits that corporate diversity, especially during times of heightened air pollution, can foster pro-social behavior in companies, with a notable impact stemming from the increasing presence of female directors on boards. Taglialatela et al. [44] highlighted the pivotal role of female directors in propelling a company's environmental sustainability efforts. From an information asymmetry standpoint, female leadership enhances the supervisory function within firms, leading to improved environmental disclosure quality, mitigating information gaps, and advancing corporate environmental transparency [45]. Moreover, considering the advisory role of female management, in the face of serious air pollution challenges, female leaders are more inclined to boost investments in environmental conservation and actively embrace corporate social responsibility, aiding in the preservation of the company's green image [46]. Cosma et al. [47] concurred with this perspective, introducing the notion of "green directors" who demonstrate a heightened commitment to environmental stewardship when confronted with ecological issues. Therefore, even in the context of poor air quality, female directors might be more supportive of environmental initiatives and social responsibilities within a company. The "green reputation" fostered by "green directors" serves as a signal that can alleviate the negative impacts of air pollution on the company's various facets. Thus, we formulate the following hypothesis.

H3(b). *Female management curbs the relationship between air pollution and CTFP.*

In summary, this paper constructs a conceptual model of the impact mechanism of air pollution on CTFP based on the above assumptions, as shown in Figure 1.

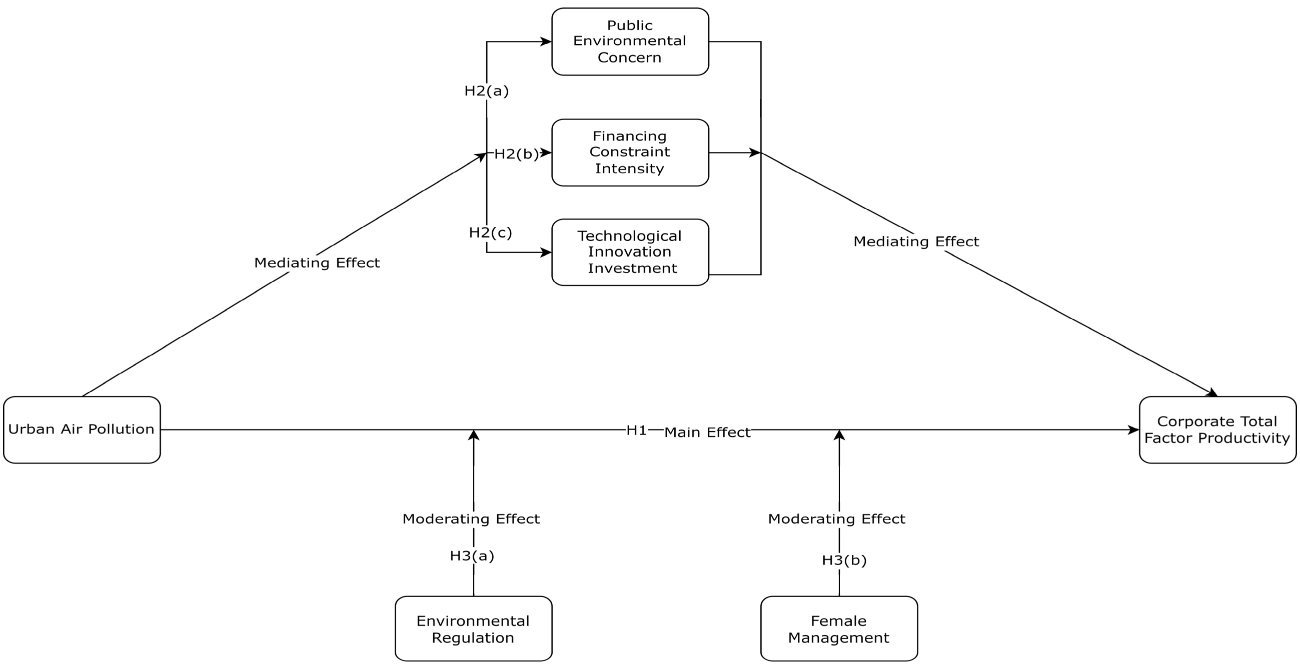

Figure 1. Conceptual model of the impact mechanisms of air pollution on CTFP.

3. Data and Method

3.1. Data Collection

To enhance the integrity and reliability of our research, we excluded companies designated with "special treatment" labels, which indicate unusual financial circumstances or incomplete datasets. This process resulted in 1308 valid observations from 218 distinct firms. Data pertinent to CTFP were extracted from the China Stock Market & Accounting Research (CSMAR) Database. Information regarding the Air Quality Index (AQI) was acquired from an air quality monitoring platform (https://www.aqistudy.cn/ (accessed on 22 April 2024)). Geographical coordinates for each city were retrieved via a map-based Application Programming Interface (API). The assessment of environmental regulation drew upon data from the National Bureau of Statistics (NBS) Database, while the public environmental concern metrics were compiled from Baidu.com. Additional financial data required for the analysis were also sourced from the CSMAR Database. For the data processing and analysis, Stata17 software was employed.

3.2. Variable Identification

3.2.1. Dependent Variables

This study focuses on CTFP as the dependent variable. Investment levels are utilized as a proxy for productivity within a control function approach. The natural logarithm of the residuals from fitting the production function serves as a measure to evaluate CTFP. Aligning with the methodologies of Lu and Lian [48], intermediate inputs are employed as an alternative proxy for productivity, with the log-transformed final values of all the variables computed after incrementing the continuous variables by one. To calculate CTFP_lp, the logarithm of the residual value from the fit is used. Additionally, CTFP_ols and CTFP_fix are derived as proxies for the dependent variable using the ordinary least squares (OLS) method and a fixed-effect model, respectively, providing diverse perspectives on the productivity measurement.

3.2.2. Independent Variables

Drawing on the findings of Benchrif et al. [49], this study employs the AQI as the independent variable to investigate its relationship with CTFP. The AQI is divided into six levels, with values ranging from 0 to 50, 51 to 100, 101 to 150, 151 to 200, 201 to 300, and above 300. The larger the index and the higher the level, the more serious the pollution and the more obvious the impact on human health. Given China's substantial reliance on coal for centralized heating, the emissions of various pollutants, including sulfur dioxide (SO_2), carbon monoxide (CO), dust, and particulate matter, are significant contributors to the degradation of urban air quality. To scrutinize the baseline regression outcomes, this research utilizes PM2.5, PM10, SO_2, and CO as proxy variables for the independent variable, the AQI. Elevated levels of these pollutants indicate deteriorating urban air quality, serving as a quantifiable measure of the environmental conditions impacting corporate productivity.

3.2.3. Moderating Variables

Following the methodology delineated by Wu et al. [50], this study utilizes the proportion of funds designated for industrial pollution control to the total assets of large-scale industrial firms as a metric to gauge the intensity of environmental regulations. Furthermore, this research investigates the potential moderating effects of female leadership on the nexus between air pollution and CTFP, employing the percentage of female executives as a proxy for female leadership presence.

3.2.4. Mediating Variables

With the swift expansion of the internet, it has emerged as an essential medium for public engagement with significant societal issues. Informed by the research of Ren and Ren [51], this study adopts "environmental pollution" as a key term and uses Baidu's annual search index to quantify public environmental concern. Moreover, to explore the mediating effects of financing constraints and technological innovation investments, this paper applies the SA index to assess financing limitations and employs the natural logarithm of one plus the investment in technological innovation as an indicator of investment intensity.

3.2.5. Control Variables

We refer to the research of Li and Zhang [21] to present control variables at primarily the firm level, encompassing the firm size, growth rate, management shareholding ratio, average management age, and CEO duality. The designated variables featured in this article are outlined in Table 1.

Table 1. Variable definitions and descriptive statistics.

Variable Category	Specific Indicator	Signs	Variable Description	Data Source	Mean	Min	Max
Dependent variable	Corporate total factor productivity	CTFP	Calculated using the estimation method proposed by Lu and Lian [48]	CSMAR Database	7.026	3.524	9.483
Independent variable	Air pollution levels	AQI	Air Quality Index	Online platform monitoring and analyzing air quality	82.33	42.17	146.8
Moderating variables	Environmental regulation	Enr	Ratio of completed investment in industrial pollution control to assets of industrial enterprises above scale	NBS Database	2.11×10^{-3}	8.92×10^{-5}	2.05×10^{-2}
	Female leadership	Fem	Ratio of female managers to total management	CSMAR Database	0.164	0	0.600
Mediating variables	Public environmental concern	Pec	Baidu annual search index with environmental pollution as keyword	Baidu.com	318.4	8.699	1118
	Financing constraint intensity	Fci	SA index	CSMAR Database	−3.911	−4.560	−2.762
	Technological innovation investment	Tii	Natural logarithm of technological innovation investment plus 1		7.991	4.545	10.13
Control variables	Company size	Size	Logarithm of total assets	CSMAR Database	9.947	8.711	11.59
	Growth rate	Growth	Growth rate of operating income		1.034	−1.748	865.9
	Management shareholding	Mhr	Management's share of total shares		0.0355	0	0.731
	Average age of management	MAge	Average age of management		50.87	43.07	58.78
	CEO duality	CEO	The chairperson and general manager are the same person is assigned as 1, otherwise 0		0.161	0	1

3.3. Research Method

3.3.1. Test for Cut-Off Effects

To prevent any estimation bias, this paper presents linear and polynomial functions of the driving variable (L) to estimate the cut-off effect when using three bandwidth estimation methods: the Calonico, Cattaneo and Titiunik (CCT) method, the Imbens and Kalyanaraman (IK) method, and the cross-validation (CV) method. Therefore, the bandwidth estimation method and polynomial function need to be determined. This paper employs the "Qinling-Huaihe" River line as an instrumental variable, with a latitude range of 33.03° to 34.24°. Following the approach of Ding et al. [1], the latitude of the dividing line is determined as its mean value of 33.64°. The estimation results for the CTFP cut-off effect are shown below. The coefficients of the linear, quadratic, and cubic functions using the CCT method are insignificant. The coefficients of the linear and quadratic functions are not significant, whereas the coefficient of the cubic function is significant at the 10% significance level when using the IK method. The linear function coefficient is significant at the 10% level, the quadratic function fitting coefficient is significant at the 1% level, and the cubic function coefficient is not significant when using the CV method. Therefore, the quadratic function is employed to estimate the cut-off effect of CTFP, while the CV method is utilized to obtain the optimal bandwidth for CTFP, which is 11.33.

The cut-off effect estimation results for the AQI are shown below. When using the CCT method, the linear function coefficient is significant at the 10% level, and the quadratic and cubic function coefficients are significant at the 1% level. When using the IK method, the linear function coefficient is significant at the 10% level, the quadratic function coefficient is significant at the 1% level and the cubic function coefficient is not significant. When using the CV method, the linear and quadratic function coefficients are significant at the 1% level, and the cubic function coefficient is not significant. Therefore, we use the quadratic function to estimate the cut-off effect of the AQI, and the optimal bandwidth of the AQI of 3.12 is obtained using the CCT method. The cut-off effects of CTFP and the AQI at the "Qinling-Huaihe" River line are shown in Figure 2. The red line represents the kernel-weighted quadratic function fitting result for the entire sample, and the blue line is the linear function fitting result for the entire sample in the bandwidth interval.

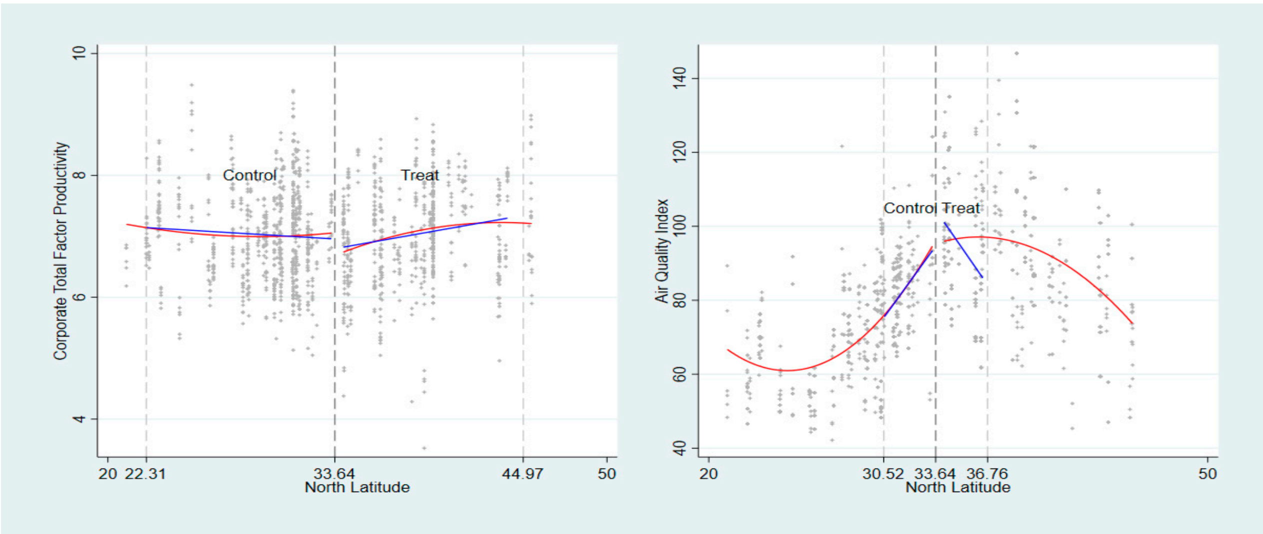

Figure 2. Cut-off effects of CTFP and the AQI at the "Qinling-Huaihe" River line.

According to Figure 2, there are discontinuous changes in both CTFP and the AQI on either side of the cut-off point. The details are as follows. CTFP has an obvious downwards jump at the demarcation line, indicating that CTFP in the north is significantly lower than in the south. Meanwhile, the AQI shows an upwards spike at the demarcation line, indicating that air pollution levels in northern cities are higher than those in southern cities. Therefore, we can tentatively conclude that there is a causal relationship between CTFP and the AQI, which also demonstrates the applicability of the RDD in this paper.

3.3.2. Model Construction

To demonstrate the superiority of the regression discontinuity design, the effect of air pollution on CTFP is first estimated using the OLS method, and the model is set as in Equation (1).

$$\mathrm{CTFP_{ict}} = \alpha_0 + a_1\mathrm{AQI_{ict}} + \alpha_2\mathrm{Controls_{ict}} + \varepsilon_{ict} \quad (1)$$

Based on the quasi-natural experiment of the centralized heating policy in northern winter, we categorize firms located in the area north of the demarcation line as the treatment group and firms located in the area south of the demarcation line as the control group, and the treatment variable is set as in Equation (2).

$$\mathrm{North_c} = \begin{cases} 1, & \mathrm{L_c} \geq 0 \\ 0, & \mathrm{L_c} < 0 \end{cases} \quad (2)$$

To test whether there is a cut-off effect of the AQI and CTFP at the dividing line, we construct the regression model as in Equations (3) and (4). Meanwhile, to avoid bias, we introduce the polynomial adjustment function of the driving variables into the equation. Additionally, the instrumental variable used is the "Qinling-Huaihe" River dividing line. Therefore, Equation (4) represents the first-stage regression model.

$$\mathrm{CTFP_{ict}} = \beta_0 + \beta_1\mathrm{North_c} + \beta_2\mathrm{f(L_c)} + \beta_3\mathrm{Controls_{ict}} + \varepsilon_{ict} \quad (3)$$

$$\mathrm{AQI_{ict}} = \gamma_0 + \gamma_1\mathrm{North_c} + \gamma_2\mathrm{f(L_c)} + \gamma_3\mathrm{Controls_{ict}} + \varepsilon_{ict} \quad (4)$$

The fitted values obtained from Equation (4) are introduced into the second-stage regression model to analyze the relationship between air pollution and CTFP. The second-stage regression model is set up as in Equation (5).

$$\mathrm{CTFP_{ict}} = \delta_0 + \delta_1\mathrm{AQI_{ict}} + \delta_2\mathrm{f(L_c)} + \delta_3\mathrm{Controls_{ict}} + \varepsilon_{ict} \quad (5)$$

This study explores the potential mediating roles of public environmental concern, the intensity of financing constraints, and investment in technological innovation in the dynamic between the AQI and CTFP. To investigate these relationships, Equation (6) is utilized to scrutinize the cut-off effect of public environmental concern. Subsequently, Equation (7) delineates a second-stage regression model to assess the influence of the AQI on public environmental concern. Equation (8) is deployed to evaluate the cut-off effect of financing constraint intensity, while Equation (9) serves as a second-stage regression model to explore the impact of the AQI on the intensity of financing constraints. Equation (10) is employed to assess the cut-off effect of investment in technological innovation, and Equation (11) constitutes a second-stage regression model for analyzing the influence of the AQI on technological innovation investment.

$$\mathrm{Pec_{ict}} = \zeta_0 + \zeta_1\mathrm{North_c} + \zeta_2\mathrm{f(L_c)} + \zeta_3\mathrm{Controls_{ict}} + \varepsilon_{ict} \quad (6)$$

$$\mathrm{Pec_{ict}} = \eta_0 + \eta_1\mathrm{AQI_{ict}} + \eta_2\mathrm{f(L_c)} + \eta_3\mathrm{Controls_{ict}} + \varepsilon_{ict} \quad (7)$$

$$\mathrm{Fci_{ict}} = \theta_0 + \theta_1\mathrm{North_c} + \theta_2\mathrm{f(L_c)} + \theta_3\mathrm{Controls_{ict}} + \varepsilon_{ict} \quad (8)$$

$$\mathrm{Fci_{ict}} = \lambda_0 + \lambda_1\mathrm{AQI_{ict}} + \lambda_2\mathrm{f(L_c)} + \lambda_3\mathrm{Controls_{ict}} + \varepsilon_{ict} \quad (9)$$

$$\mathrm{Tii_{ict}} = \mu_0 + \mu_1\mathrm{North_c} + \mu_2\mathrm{f(L_c)} + \mu_3\mathrm{Controls_{ict}} + \varepsilon_{ict} \quad (10)$$

$$\mathrm{Tii_{ict}} = \nu_0 + \nu_1\mathrm{AQI_{ict}} + \nu_2\mathrm{f(L_c)} + \nu_3\mathrm{Controls_{ict}} + \varepsilon_{ict} \quad (11)$$

Environmental regulation and female leadership are incorporated as moderating variables, with the model integrating an interaction term between these moderating variables and the independent variables. The evaluation of a moderating effect is determined by the statistical significance of the interaction term's coefficient. Equations (12) and (13) define the initial-stage regression models employed to examine the moderating role of environmental regulations. The second-stage regression model, which includes the interaction term between environmental regulation and the AQI, is articulated in Equation (14). For the examination of female leadership's moderating influence, Equations (15) and (16) outline the initial-stage regression models. The introduction of the interaction term between female leadership and the AQI in Equation (17) forms the basis of the second-stage regression model.

$$AQI_{ict} = \xi_0 + \xi_1 North_c + \xi_2 Enr_{ict} + \xi_3 North_c \times Enr_{ict} + \xi_4 f(L_c) + \xi_5 Controls_{ict} + \varepsilon_{ict} \tag{12}$$

$$AQI_{ict}{*}Enr_{ict} = \rho_0 + \rho_1 North_c + \rho_2 Enr_{ict} + \rho_3 North_c \times Enr_{ict} + \rho_2 f(L_c) + \rho_3 Controls_{ict} + \varepsilon_{ict} \tag{13}$$

$$TFP_{ict} = \tau_0 + \tau_1 AQI_{ict} + \tau_2 Enr_{ict} + \tau_2 AQI_{ict} \times Enr_{ict} + \tau_2 f(L_c) + \tau_3 Controls_{ict} + \varepsilon_{ict} \tag{14}$$

$$AQI_{ict} = \upsilon_0 + \upsilon_1 North_c + \upsilon_2 Fem_{ict} + \upsilon_3 North_c \times Fem_{ict} + \upsilon_4 f(L_c) + \upsilon_5 Controls_{ict} + \varepsilon_{ict} \tag{15}$$

$$AQI_{ict}{*}Fem_{ict} = \varphi_0 + \varphi_1 North_c + \varphi_2 Enr_{ict} + \varphi_3 North_c \times Enr_{ict} + \varphi_2 f(L_c) + \varphi_3 Controls_{ict} + \varepsilon_{ict} \tag{16}$$

$$CTFP_{ict} = \omega_0 + \omega_1 AQI_{ict} + \omega_2 Fem_{ict} + \omega_2 AQI_{ict} \times Fem_{ict} + \omega_2 f(L_c) + \omega_3 Controls_{ict} + \varepsilon_{ict} \tag{17}$$

where i denotes firms; t denotes years; c denotes cities; L_c denotes the running valuable, which is the difference between the latitude of the city where the company is located and the dividing line; the treatment variable, denoted by $North_c$, equals 1 if the firm is located north of the dividing line, and 0 otherwise.; $f(L_c)$denotes the polynomial adjustment function of the running variable; α_0, β_0, γ_0, δ_0, ζ_0, η_0, θ_0, λ_0, μ_0, ν_0, ξ_0, ρ_0, τ_0, υ_0, φ_0 and ω_0 denote constant terms; $\alpha_1 - \alpha_2$, $\beta_1 - \beta_3$, $\gamma_1 - \gamma_3$, $\delta_1 - \delta_3$, $\zeta_1 - \zeta_3$, $\eta_1 - \eta_3$, $\theta_1 - \theta_3$, $\lambda_1 - \lambda_3$, $\mu_1 - \mu_2$, $\nu_1 - \nu_3$, $\xi_1 - \xi_5$, $\rho_1 - \rho_5$, $\tau_1 - \tau_5$, $\upsilon_1 - \upsilon_5$, $\phi_1 - \varphi_5$ and $\omega_1 - \omega_5$ denote variable coefficients; Controls denotes the control variables set and ε_{ict} denotes the random disturbance term.

4. Results

4.1. Baseline Regression

To evaluate the applicability of the RDD in this research, the OLS methodology is applied to ascertain the relationship between air pollution and CTFP. The findings from Model (1) in Table 2 indicate a significant negative influence of the AQI on CTFP at the 1% significance level. To address the potential endogeneity, this study incorporates the RDD alongside the 2SLS approach to further scrutinize the effect of air pollution on CTFP. Additionally, a quadratic term for the running variable is integrated into the regression model following the Akaike Information Criterion (AIC). The initial estimation phase, depicted in Models (2) and (3), reveals significant regional disparities in the CTFP and AQI levels. Specifically, Model (2) illustrates that firms in the northern region exhibit markedly lower CTFP compared to their southern counterparts at the 1% level. Conversely, Model (3) shows that the AQI in the north significantly exceeds that in the south, also at the 1% level. The findings from Model (4), representing the second-stage estimation, confirm a substantial negative impact of air pollution on CTFP at the 1% level, thus strongly supporting H1. Furthermore, the instrumental variable successfully passes the tests of unidentifiability and weak identification, affirming its validity. The analysis also reveals that the impact coefficient of air pollution on CTFP in Model (4) is smaller than that in Model (1), suggesting that the OLS estimates might significantly understate the negative effects of air pollution on CTFP, potentially leading to biased results. Additionally, this study observes that firm size has a significant positive influence on CTFP at the 1% level, aligning with financing constraint theories, which posit that larger firms face fewer growth impediments. A significant negative relationship is also identified between the average age of management and CEO duality with CTFP, indicating that younger management and clear delineation of leadership roles could foster increased CTFP.

Table 2. Impact of air pollution on CTFP.

Dep. Variable	Model (1)	Model (2)	Model (3)	Model (4)
	OLS	First Stage		Second Stage
	CTFP	CTFP	AQI	CTFP
North		−0.096 ***	20.226 ***	
		(−3.13)	(24.47)	
AQI	−0.003 ***			−0.005 ***
	(−4.00)			(−3.14)
Size	1.102 ***	1.104 ***	−0.539	1.101 ***
	(36.11)	(36.14)	(−0.65)	(36.14)
Growth	−0.000	−0.000	0.018	−0.000
	(−0.60)	(−0.62)	(1.04)	(−0.49)
Mhr	−0.085	−0.083	2.332	−0.072
	(−0.50)	(−0.48)	(0.51)	(−0.42)
MAge	−0.016 ***	−0.016 ***	0.115	−0.016 ***
	(−2.74)	(−2.81)	(0.74)	(−2.71)
CEO	−0.138 ***	−0.124 ***	−2.731 **	−0.137 ***
	(−3.27)	(−2.92)	(−2.39)	(−3.20)
Polynomial in L		Quadratic	Quadratic	Quadratic
Intercept	−2.834 ***	−3.107 ***	78.228 ***	−2.735 ***
	(−7.58)	(−8.39)	(7.84)	(−7.16)
Under-identification test LM statistic				412.46
*p*_value				0.000 ***
Weak identification test Wald F statistic				598.73
No. Observations	1308	1308	1308	1308
R-Squared	0.516	0.518	0.381	0.516

Note: **, *** significant at the 5% and 1% confidence levels, respectively, with *t*-stats in parentheses, the same below.

4.2. Robustness Tests

4.2.1. Continuity Test for Covariates

The application of the RDD presupposes the continuity of covariates at the designated cut-off point. This continuity is imperative to ascertain that the observed effect on CTFP at the cut-off is not influenced by the control variables. The outcomes of the analysis, as presented in Table 3, reveal that the covariates do not demonstrate significant deviations at the cut-off, underscoring their consistent and uninterrupted nature at this juncture. This observation supports the conclusion that the covariates maintain a stable and continuous presence at the cut-off point, validating the application of the RDD in this context.

Table 3. Continuity test of covariates.

Covariates	Size	Growth	Mhr	MAge	CEO
Cut-off effects of covariates	−0.060	−0.412	−0.011	0.756	−0.155
	(−0.58)	(−0.85)	(−0.52)	(1.01)	(−1.60)

4.2.2. Manipulation Test for Running Variable

This paper utilizes the rddensity command created by Cattaneo et al. [52] to generate a density plot for the running variable manipulation test. As depicted in Figure 3, the majority of the confidence intervals of the density functions on either side of the cut-off point largely overlap. Meanwhile, the *p*_value is 0.1928, indicating an inability to reject the null hypothesis that the sample sizes of the two sides near the cut-off point are roughly equal. This indicates that the density function of the running variable is continuous at the cut-off point and has not been tampered with.

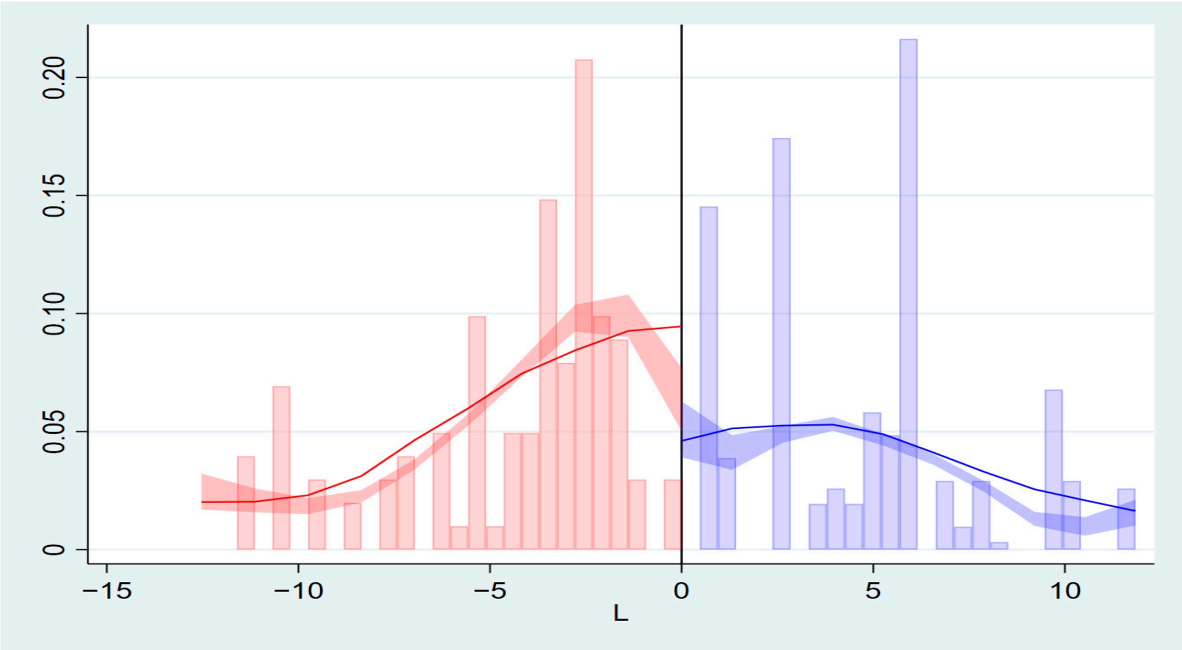

Figure 3. Density function diagram for running variable.

4.2.3. Sensitivity Test for Bandwidth Selection

The bandwidth selection significantly affects the sample size and the estimation of the average treatment effect's potential bias. In the baseline regression analysis, the entire sample is utilized for estimation purposes. However, to verify the robustness of the baseline results, it is essential to demonstrate that air pollution consistently exerts a significant negative effect on CTFP across a range of bandwidths. Utilizing the CV method, the optimal bandwidth for CTFP is determined to be 11.33. Table 4 presents the estimation outcomes from Models (1)–(4), which employ bandwidths at 0.3, 0.5, 0.7, and 0.9 times the optimal value, respectively. Panel (A) illustrates that, under various bandwidth settings, CTFP in the north remains significantly lower than in the south at the 1% level. Panel (B) details the first-stage estimation results, highlighting that the AQI in the north is significantly greater than that in the south at the 1% level. Panel (C) conveys the second-stage estimation findings, indicating that air pollution consistently negatively affects CTFP at the 1% level across the different bandwidths. These results affirm that the choice of bandwidth size does not compromise the baseline regression results' reliability.

Table 4. Sensitivity test for bandwidth selection.

Panel	**Model (1)**	**Model (2)**	**Model (3)**	**Model (4)**
	Bandwidth			
	3.399	**5.665**	**7.931**	**10.197**
Panel (A)	CTFP			
North	−0.201 ***	−0.162 ***	−0.100 ***	−0.113 ***
	(−4.25)	(−4.41)	(−3.10)	(−3.47)
R-Squared	0.596	0.571	0.543	0.515
Panel (B)	AQI			
North	8.932 ***	17.807 ***	21.528 ***	21.754 ***
	(7.30)	(17.29)	(24.01)	(24.89)
R-Squared	0.289	0.293	0.370	0.379

Table 4. *Cont.*

Panel	**Model (1)**	**Model (2)**	**Model (3)**	**Model (4)**
	Bandwidth			
	3.399	**5.665**	**7.931**	**10.197**
Panel (C)	CTFP			
AQI	−0.023 ***	−0.009 ***	−0.005 ***	−0.005 ***
	(−3.82)	(−4.34)	(−3.10)	(−3.47)
Control variables	Yes	Yes	Yes	Yes
Polynomial in L	Quadratic	Quadratic	Quadratic	Quadratic
Intercept	−2.846 ***	−3.458 ***	−2.957 ***	−2.534 ***
	(−3.29)	(−7.05)	(−7.52)	(−6.36)
R-Squared	0.494	0.553	0.541	0.512
Under-identification test LM statistic	49.390	224.294	382.552	410.009
*p*_value	0.000 ***	0.000 ***	0.000 ***	0.000 ***
Weak identification test Wald F statistic	53.228	298.964	576.326	619.715
No. Observations	582	874	1122	1196

Note: *** significant at the 1% confidence levels, respectively, with *t*-stats in parentheses, the same below.

4.2.4. Independent and Dependent Variables Replacement

The robustness tests performed in this study, as detailed in Table 5, involve varying the independent and dependent variables to confirm the stability and reliability of the initial findings. In Panel (A), Models (1)–(3) showcase the comparative analysis of air quality between the northern and southern regions, demonstrating a significantly higher AQI in the north compared to the south at the 1% level. This indicates more severe air pollution in the northern regions. Subsequently, Models (4)–(6) explore the regional differences in CTFP, revealing that the productivity in the north is significantly lower than in the south, also at the 1% level. These results underscore the geographic disparity in both air pollution levels and corporate productivity across these regions. Panel (B) details the second-stage estimation results, where all the models uniformly indicate that air pollution negatively influences CTFP at the 1% level. This consistent finding across various models and proxy variables reinforces H1—namely, that air pollution detrimentally affects CTFP.

4.2.5. Instrument Variable Replacement

The "Qinling-Huaihe" River is the demarcation line of 800 mm annual precipitation. Li et al. [53] have highlighted that precipitation can reduce airborne particulate matter, generally linking higher precipitation rates with improved air quality. This research employs the air flow coefficient (AFC) and temperature inversion (TEI) as instrumental variables for air quality, inspired by the methodologies of Sager [54] and Zhu and Lee [55]. These environmental factors, precipitation, AFC, and TEI, are crucial because they are naturally occurring and not influenced by economic activities, thereby meeting the exogeneity requirement for instrumental variables. Temperature inversion data were sourced from the National Aeronautics and Space Administration (NASA), and AFC data were obtained from the climate reanalysis dataset (ERA-Interim). In Table 6, Models (1)–(3) provide the estimation results using precipitation, AFC, and TEI as instrumental variables independently. Panel (A) unveils the primary estimation results, showing a decrease in the AQI with an increase in precipitation and AFC, suggesting cleaner air conditions. Conversely, a rise in the temperature inversion correlates with heightened pollution levels. Panel (B) offers insights from the second-stage estimation, where Models (1)–(3) successively demonstrate that air pollution adversely impacts CTFP, with significant negative effects observed at the 10%, 5%, and 1% levels, respectively, when using the different instrumental variables.

By utilizing natural environmental variables as instrumental proxies, this study provides robust evidence of the negative effects of air pollution on CTFP.

Table 5. Independent and dependent variable replacement.

Panel	Model (1)	Model (2)	Model (3)	Model (4)	Model (5)	Model (6)
	Independent Variables Replacement			Dependent Variables Replacement		
Panel (A)	PM2.5	PM10	SO_2	CTFP_lp	CTFP_ols	CTFP_fixed
North	13.242 ***	27.988 ***	7.011 ***	−0.134 ***	−0.145 ***	−0.150 ***
	(17.77)	(24.85)	(12.89)	(−4.25)	(−4.71)	(−4.81)
R-Squared	0.247	0.373	0.132	0.708	0.794	0.807
Panel (B)		CTFP		TFP_lp	TFP_ols	TFP_fixed
AQI				−0.007 ***	−0.007 ***	−0.007 ***
				(−4.21)	(−4.65)	(−4.75)
PM2.5	−0.007 ***					
	(−3.14)					
PM10		−0.003 ***				
		(−3.17)				
SO_2			−0.014 ***			
			(−3.08)			
Control variables	Yes	Yes	Yes	Yes	Yes	Yes
Polynomial in L	Quadratic	Quadratic	Quadratic	Quadratic	Quadratic	Quadratic
Intercept	−2.732 ***	−2.741 ***	−2.439 ***	−6.162 ***	−8.081 ***	−8.679 ***
	(−7.15)	(−7.25)	(−5.75)	(−15.57)	(−20.77)	(−22.02)
R-Squared	0.516	0.524	0.498	0.701	0.788	0.802
Under-identification test LM statistic	255.566	421.303	148.259	412.456	412.456	412.456
*p*_value	0.000 ***	0.000 ***	0.000 ***	0.000 ***	0.000 ***	0.000 ***
Weak identification test Wald F statistic	315.683	617.680	166.189	598.734	598.734	598.734
No. Observations	1308	1308	1308	1308	1308	1308

Note: *** significant at the 1% confidence levels, respectively, with *t*-stats in parentheses, the same below.

Table 6. Results of instrument variable replacement.

Panel	Model (1)	Model (2)	Model (3)
	Precipitation	Air Flow Coefficient	Temperature Inversion
Panel (A)		AQI	
Precipitation	−13.350 ***		
	(−17.72)		
AFC		−0.003 ***	
		(−3.21)	
TEI			11.579 ***
			(16.09)
R-Squared	0.271	0.103	0.246
Panel (B)		CTFP	
AQI	−0.004 *	−0.034 **	−0.006 ***
	(−1.85)	(−2.48)	(−2.79)
Control variables	Yes	Yes	Yes
Polynomial in L	Quadratic	Quadratic	Quadratic
Intercept	−2.812 ***	−0.857	−2.665 ***
	(−7.23)	(−0.84)	(−6.76)
R-Squared	0.517	0.021	0.513

Table 6. *Cont.*

Panel	Model (1)	Model (2)	Model (3)
	Precipitation	**Air Flow Coefficient**	**Temperature Inversion**
Under-identification test LM statistic p_value	254.420 0.000 ***	10.294 0.001 ***	217.156 0.000 ***
Weak identification test Wald F statistic	313.926	10.312	258.794
No. Observations	1308	1308	1308

Note: *, **, *** significant at the 10%, 5% and 1% confidence levels, respectively, with *t*-stats in parentheses, the same below.

4.3. Heterogeneity Analysis

This paper delves into the nuanced effects of air pollution on CTFP by examining three distinct aspects: environmental attributes, regional characteristics, and green branding. The analysis in Table 7 is structured into two panels, where Panel (A) presents the initial estimation results and Panel (B) details the findings from the subsequent stage. Following the categorization by Ding et al. [1], industries are classified into heavy and non-heavy polluters. The analysis in Models (1)–(2) reveals that air pollution significantly undermines the CTFP of heavily polluting firms at the 1% level. In contrast, for firms categorized as not heavily polluting, air pollution's impact on CTFP is negative but not statistically significant. This discrepancy can be attributed to the heavier financial and regulatory burdens that more-polluting firms face as air pollution intensifies. From a regional perspective, Models (3)–(4) assess the relationship between air pollution and CTFP. The results indicate a non-significant adverse effect of air pollution on eastern firms' CTFP, whereas for firms in the less economically developed non-eastern regions, air pollution significantly decreases CTFP at the 5% level. The investment diversion from technological innovation to pollution control in these less affluent regions is more pronounced, exacerbating the negative impact on CTFP. The analysis extends to green branding, distinguishing firms with ISO14001 certification (high green branding) from those without it (low green branding). According to Models (5)–(6), air pollution negatively affects the CTFP of high green branding firms, albeit insignificantly. Conversely, firms with low green branding experience a significant and adverse effect on CTFP at the 1% level. This outcome aligns with signaling theory, where the lack of ISO14001 certification can erode consumer trust and investor confidence, further impeding CTFP.

Table 7. Heterogeneity tests of environmental attributes, regional characteristics and green branding.

Panel	Model (1)	Model (2)	Model (3)	Model (4)	Model (5)	Model (6)
	Environmental Attribute		**Regional Characteristic**		**Green Branding**	
	Heavy	**Non-Heavy**	**Eastern**	**Non-Eastern**	**High**	**Low**
Panel (A)	AQI					
North	17.660 *** (13.88)	22.274 *** (19.65)	21.529 *** (23.99)	19.665 *** (10.01)	20.463 *** (13.49)	20.361 *** (20.36)
R-Squared	0.360	0.404	0.416	0.357	0.406	0.373
Panel (B)	CTFP					
AQI	−0.009 *** (−2.97)	−0.002 (−1.51)	−0.002 (−1.46)	−0.009 ** (−2.57)	−0.001 (−0.23)	−0.007 *** (−3.86)
Control variables	Yes	Yes	Yes	Yes	Yes	Yes
Polynomial in L	Quadratic	Quadratic	Quadratic	Quadratic	Quadratic	Quadratic
Intercept	−2.624 *** (−3.35)	−2.402 *** (−5.70)	−3.116 *** (−7.05)	−1.898 ** (−2.45)	−3.059 *** (−4.10)	−2.474 *** (−5.51)
R-Squared	0.447	0.585	0.519	0.530	0.521	0.515

Table 7. *Cont.*

Panel	Model (1)	Model (2)	Model (3)	Model (4)	Model (5)	Model (6)
	Environmental Attribute		**Regional Characteristic**		**Green Branding**	
	Heavy	**Non-Heavy**	**Eastern**	**Non-Eastern**	**High**	**Low**
Under-identification test LM statistic	144.652	256.880	371.373	75.091	125.589	287.460
*p*_value	0.000 ***	0.000 ***	0.000 ***	0.000 ***	0.000 ***	0.000 ***
Weak identification test Wald F statistic	192.589	386.265	575.644	100.166	181.867	414.462
No. Observations	557	751	1032	276	388	920

Note: **, *** significant at the 5% and 1% confidence levels, respectively, with *t*-stats in parentheses, the same below.

4.4. Expanded Analysis

4.4.1. Mediating Effects

This study delves into how air pollution influences CTFP through the lens of three mediating variables: public environmental concern, intensity of financing constraints, and investment in technological innovation. In Table 8, Panel (A) presents the first-stage estimation outcomes, showing that in the north, public environmental concern and financing constraints are elevated, while investment in technological innovation is comparatively lower. Panel (B) details the second-stage estimation results. Model (1) reveals that air pollution significantly escalates public environmental concern at the 1% level, suggesting that increased air pollution heightens public awareness of and demand for greener products. This shift prompts firms to allocate more resources toward eco-friendly production, potentially at the expense of other business activities, thereby adversely affecting CTFP. This result robustly supports H2(a). Model (2) finds that air pollution intensifies financing constraints at the 1% level, indicating that as financial pressures mount due to air pollution, firms' resource allocations dwindle, leading to a downturn in productivity. This observation fully corroborates H2(b). Model (3) shows that air pollution negatively affects investment in technological innovation at the 1% level. Since technological innovation is pivotal for corporate growth and high-quality development, reduced investment in this area, spurred on by air pollution, hampers CTFP enhancement. This finding lends complete support to H2(c).

4.4.2. Moderating Effects

This paper examines how external environmental regulations and the gender diversity of firm management influence the relationship between air pollution and CTFP. The findings, as shown in Table 9, indicate that both environmental regulations and female leadership within firms significantly moderate the impact of air pollution on CTFP. In the analysis, Models (1)–(2) showcase the first-stage regression results that assess the moderating effect of environmental regulations on the air pollution–CTFP relationship. The results from Model (3), the second-stage regression, reveal that the interaction term coefficient between environmental regulation and the AQI is significantly negative at the 1% level. This demonstrates that environmental regulations have a substantial positive moderating effect on mitigating the adverse impact of air pollution on CTFP, thus fully supporting H3(a). On the other hand, Models (4)–(5) detail the initial regression results exploring the moderating influence of female leadership. Model (6), the second-stage regression, shows that the interaction term coefficient between female leadership and the AQI is significantly positive at the 5% level. This outcome indicates that female leadership has a significant negative moderating effect on the relationship between air pollution and CTFP, suggesting that while female leaders may prioritize environmental initiatives, such initiatives could potentially divert resources from other core economic activities, adversely affecting CTFP. This result lends full support to H3(b).

Table 8. Mediating effects of public environmental concern, financing constraint intensity and technological innovation investment.

Panel	**Model (1)**	**Model (2)**	**Model (3)**
Panel (A)	Pec	Fci	Tii
North	71.873 ***	0.090 ***	−0.130 ***
	(5.70)	(8.10)	(−3.81)
R-Squared	0.039	0.187	0.421
Panel (B)	Pec	Fci	Tii
AQI	3.553 ***	0.004 ***	−0.006 ***
	(6.30)	(8.17)	(−3.75)
Control variables	Yes	Yes	Yes
Polynomial in L	Quadratic	Quadratic	Quadratic
Intercept	−205.722	−5.632 ***	−1.446 ***
	(−1.44)	(−40.88)	(−3.33)
R-Squared	0.208	0.196	0.398
Under-identification test LM statistic	412.456	412.456	412.456
*p*_value	0.000 ***	0.000 ***	0.000 ***
Weak identification test Wald F statistic	598.734	598.734	598.734
No. Observations	1308	1308	1308

Note: *** significant at the 1% confidence levels, respectively, with *t*-stats in parentheses, the same below.

Table 9. Moderating effects of environmental regulation and female leadership.

Panel	**Model (1)**	**Model (2)**	**Model (3)**	**Model (4)**	**Model (5)**	**Model (6)**
	Environmental Regulation			**Female Leadership**		
	First Stage		**Second Stage**	**First Stage**		**Second Stage**
	AQI	**AQI× Enr**	**CTFP**	**AQI**	**AQI× Fem**	**CTFP**
North	23.953 ***	0.002 ***		22.878 ***	0.804 ***	
	(22.55)	(4.15)		(14.56)	(2.82)	
Enr	−2540.219 ***	61.896 ***	1264.363 ***			
	(−4.54)	(206.30)	(4.74)			
North × Enr	-1.05×10^4 ***	14.599 ***				
	(2.80)					
AQI			0.002			−0.011 ***
			(1.23)			(−3.43)
AQI × Enr			−19.235 ***			
			(−4.63)			
Fem				9.294	76.026 ***	−3.063 **
				(1.64)	(74.04)	(−2.01)
North × Fem				−16.210 **	14.049 ***	
				(−1.98)	(9.45)	
AQI × Fem						0.039 **
						(2.09)
Control variables	Yes	Yes	Yes	Yes	Yes	Yes
Polynomial in L	Quadratic	Quadratic	Quadratic	Quadratic	Quadratic	Quadratic
Intercept	94.342 ***	0.006	−3.218 ***	76.150 ***	3.570 *	−2.498 ***
	(9.48)	(1.17)	(−8.04)	(7.16)	(1.85)	(−5.78)
R-Squared	0.411	0.975	0.506	0.383	0.908	0.512
Under-identification test LM statistic			334.507			292.473
*p*_value			0.000 ***			0.000 ***
Weak identification test Wald F statistic			223.006			186.913
No. Observations	1308	1308	1308	1308	1308	1308

Note: *, **, *** significant at the 10%, 5% and 1% confidence levels, respectively, with *t*-stats in parentheses, the same below.

5. Discussion

This paper develops an RDD with 2SLS to investigate the causal pathway of air pollution regarding CTFP. We investigate the impact of air pollution on CTFP and find a significant and negative relationship. This relationship is mediated by levels of public environmental concern, intensity of financing constraints, and investment in technological innovation. We also identify heterogeneity in the relationship between air pollution and CTFP. However, the reasons for this heterogeneity require further discussion.

(1) The influence of air pollution on CTFP is particularly pronounced in sectors characterized by high pollution levels and low green branding. Energy-intensive and asset-heavy enterprises, often categorized as high polluters, significantly dictate their economic activities in response to increased air pollution. The classification of companies as “polluting” based on their inability to secure ISO14001 certification can considerably affect consumer trust in products and investor confidence in the capital markets, as explained by signaling theory [56]. This negative perception, in turn, detrimentally impacts CTFP. The government, acting as the regulator and monitor of environmental pollution, intensifies environmental regulations and enforces large-scale interventions during periods of high pollution. Such regulatory measures aim to encourage environmentally friendly modifications of corporate industrial structures, improving their layout and upgrading production technology, thereby mitigating pollution from high-emission industries. However, companies with significant environmental footprints and lacking green credentials are likely to face increased regulatory attention in areas with severe pollution levels. While there is a pressing need to augment environmental investments, it is crucial that these investments do not undermine routine business operations, as this could ultimately impair CTFP.

(2) With rising public environmental consciousness and higher education levels, there is an escalating demand for green and low-carbon lifestyles. Concurrently, advancements in internet technology have amplified the media’s capacity to scrutinize environmental issues, compelling companies to actively fulfill their social responsibilities. Nonetheless, firms with significant pollution outputs and low green credentials often resort to “greenwashing” and deceptive corporate social responsibility (CSR) tactics to foster a favorable public image [1]. These companies face challenges due to obsolete equipment and inefficient industrial structures, where the inclination is more toward paying penalties than investing in eco-friendly industrial upgrades. This approach not only leads to environmental mishaps but also diminishes the integrity of accounting information and environmental reporting. To eschew external criticism, it is crucial for businesses to commit to environmentally sustainable practices and modernize their infrastructure. Wang and Tang [31] indicated that the introduction of environmental protection taxes and green credit policies has intensified financial and regulatory burdens on highly polluting firms with weak environmental branding. Such pressures augment financial constraints and compliance costs, thereby adversely affecting CTFP as air pollution intensifies.

(3) Subgroup regression analysis reveals that the impact of air pollution on CTFP is more pronounced in non-eastern regions. This can be attributed to the regions’ fragile ecological environment and comparatively slower economic development, which impede the growth of superior corporate practices. In an effort to foster balanced economic development across different areas, the central government has introduced initiatives aimed at revitalizing old industrial bases in the northeast, developing the western region, and promoting the rise of central China [57]. While these strategies have somewhat mitigated inter-regional economic disparities, they have not fundamentally transformed the prevalent model of extensive economic development in the central and western regions.

Technological innovation is vital for enhancing high-quality development in companies, but it is fraught with high risks, long durations, and significant capital demands. To minimize the financial risks, companies may opt for paying penalties rather than committing to green innovation, which hampers the ecological progress of industrial structures in non-eastern areas. Compared to the eastern regions, local governments in non-eastern areas show lower levels of regulatory quality, adherence to the rule of law, corruption control, and governmental effectiveness. These regions face industrial agglomeration challenges and limited enterprise development potential due to subpar institutional quality, a lack of advanced technology, and insufficient financial resources. Moreover, air pollution further deteriorates the investment environment in these areas. In line with the "pollution paradise" hypothesis, the relocation of firms due to higher regulatory and pollution control costs can diminish their clustering benefits [27]. Thus, air pollution significantly hinders the enhancement of CTFP in firms located in non-eastern regions, posing a considerable barrier to their economic advancement.

6. Conclusions

6.1. Conclusions and Implications

Leveraging the broken window theory of urban decline and the general equilibrium theory, this study delves into the repercussions of air pollution for CTFP, employing an RDD with 2SLS using panel data from Chinese manufacturing companies listed between 2015 and 2020. The initial regression outcomes indicate a significant adverse effect of air pollution on CTFP growth, thus entirely validating H1. This research further solidifies the baseline regression results through successful continuity tests of covariates, manipulation checks of running variables, and sensitivity analyses of bandwidth. By altering the independent, dependent, and instrumental variables, the robustness of the baseline findings is affirmed. Mechanistic examinations reveal that air pollution curtails CTFP by intensifying public environmental concern, amplifying financing constraint severity, and reducing technological innovation investment. These insights provide comprehensive support for H2(a), H2(b), and H2(c). Additionally, this study uncovers that while environmental regulation positively moderates the air pollution–CTFP nexus, female leadership exerts a negative moderating effect. Therefore, these findings fully support H3(a) and H3(b). Air pollution represents a global concern. This paper examines the impact of urban air quality on the total factor productivity of Chinese listed firms, with a particular focus on the implications of centralized heating policies. These findings may also be of interest to other countries or regions that implement centralized heating policies and span different temperature zones. Based on these insights, the paper presents the following recommendations for stakeholders.

(1) The government must focus on enhancing pollution control and treatment frameworks, solidifying the execution of the central environmental protection inspection mechanism, and continually improving industrial incentive schemes to cultivate an optimal environment for superior corporate growth. Given the local governments' augmented authority in China's political structure, which has inadvertently weakened the enforcement prowess of environmental agencies due to the territorial management approach [36], it is imperative to bolster the vertical management system of these bodies and the centralized inspection regime, thereby laying a strong legal groundwork for environmental stewardship. The government is also encouraged to optimize energy usage, advocate for efficient fossil fuel use, and support the advancement of clean, renewable energy sources. Enterprises are urged to adopt cleaner production techniques, innovate eco-friendly products, and champion the growth of "model" enterprises in new sectors [1]. Moreover, government departments serve as policymakers and supervisory bodies for environmental governance. It is necessary to fully utilize the market mechanism, enhance the pollution control system, and implement scientific and effective measures for air pollution prevention and control. The green GDP assessment should serve as a benchmark for evaluating the efficiency of local government governance. This guarantees the harmonization of local government and corporate performance. The reward and punishment mechanisms for

pollution control can be enhanced by utilizing macro-control. Fiscal policies, such as increased subsidies and tax reductions, should be implemented to augment the innovation incentive policy [58]. Legislation is necessary to reinforce the protection of green intellectual property rights. In turn, this will amplify the synergistic effect of the interaction of green innovation behaviors among businesses and stimulate the vitality of enterprise innovation. By leveraging environmental taxes, green insurance, and credit policies, the government can channel capital toward less polluting firms, thus facilitating continuous environmental quality enhancement and green industrial transformation [59,60]. Improving foreign investment's risk compensation and exit strategies will create an inviting business milieu, enticing more firms to contribute to environmental management.

(2) Environmental regulators need to apply varied environmental directives and refine supplementary policies for environmental management to back corporate sustainable growth. Augmenting the government's environmental information dissemination system and boosting the transparency of corporate ecological data [12] can standardize industry standards and bolster information sharing, lowering data acquisition costs and simplifying the process for investors to identify compliant businesses. Establishing a societal "collective constraint" mechanism can increase the costs for non-compliant enterprises, fostering responsible behavior across the board. Tailored environmental regulations based on regional specifics are essential, promoting synchronized progress across territories and sectors while fine-tuning policy incentives. Regulators ought to enhance the dissemination of environmental protection information in order to encourage society at all levels to adopt the principles of green, low-carbon development. Citizens are considered to be critical actors in public affairs, serving as an effective mechanism for enhancing governmental decision-making and governance. The lowering of the threshold for citizen participation in environmental protection and the full utilization of the media's monitoring and reputation mechanisms can encourage the public to adopt greener lifestyles, which will in turn increase awareness and enthusiasm for environmental protection [12,22].

(3) Corporations should set up a green innovation and research and development (R&D) platform, alongside a system for long-term performance evaluation, to consistently open up financing avenues and bolster CTFP. As reputation is a pivotal intangible asset, firms should heighten their environmental investments and actively disclose social responsibility efforts to project a green image in the capital market, potentially reducing agency costs and easing financial constraints [37]. Businesses must align their growth strategies with state innovation and environmental policies to achieve high-quality development. Responding to the call for eco-friendly consumption, firms should wisely allocate resources for production and operations, steering clear of polluting practices [61]. Establishing green innovation and R&D centers and accelerating the conversion of scientific and technological advancements into actual productivity can improve the fundamental competitiveness of businesses. Although the compensatory effect of technological innovation has a delay, managers should disregard the reduction in profit in the short term and refrain from shortsighted behaviors to a certain extent. Managers should establish a long-lasting performance feedback mechanism, which can lead to a "win–win" situation for both financial and environmental performance [57,58].

6.2. Shortcomings and Future Research Directions

This paper, having elucidated various contributions and insights, delineates future research avenues while acknowledging its limitations as follows. (1) As crucial assets for organizations, employees' high turnover rates and brain drain, exacerbated by air pollution, incur significant recruitment and training costs. Future studies are poised to delve into the mediating role of employee turnover in the air pollution–CTFP nexus, adopting a human resource management lens. (2) The stability of the institutional environment is fundamental for the seamless operation of businesses. The unpredictability of governmental economic policy adjustments, influenced by external factors, poses a challenge for companies [62]. Thus, the exploration of how economic policy uncertainty influences the interplay between air pollution and CTFP emerges as a promising research frontier. (3) Companies benefiting from government subsidies are often perceived as "green" enterprises through the lens of signaling theory, enhancing their public image and attracting investment, which in turn eases financing constraints. Future inquiries will concentrate on dissecting the "incentive effect" of such government subsidies, evaluating their impact on firms' financial health and public perception.

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Abbreviations

RDD	Regression Discontinuity Design
CTFP	Corporate Total Factor Productivity
FDI	Foreign Direct Investment
2SLS	Two-Stage Least Squares
YRD	Yangtze River Delta
GMM	Generalized Method of Moments Model
IPOs	Initial Public Offerings
CSMAR	China Stock Market & Accounting Research Database
AQI	Air Quality Index
API	Application Programming Interface
NBS	National Bureau of Statistics Database
OLS	Ordinary Least Squares
SO_2	Sulfur Dioxide
CO	Carbon Monoxide
CCT	Calonico, Cattaneo and Titiunik Method
IK	Imbens and Kalyanaraman Method
CV	Cross-Validation Method
AIC	Akaike Information Criterion
AFC	Air Flow Coefficient
TEI	Temperature Inversion
NASA	National Aeronautics and Space Administration
CSR	Corporate Social Responsibility

References

1. Ding, X.; Vukovic, D.B.; Shams, R.; Vukovic, N. Does air pollution affect corporate shareholder responsibility performance?: Analysis of regression discontinuity design based on the "Qinling-Huaihe" line. *Environ. Dev. Sustain.* **2023**, 04063. [CrossRef]
2. Jiménez-Parra, B.; Alonso-Martínez, D.; Godos-Díez, J.L. The influence of corporate social responsibility on air pollution: Analysis of Environmental Regulation and eco-innovation effects. *Corp. Soc. Responsib. Environ. Manag.* **2018**, *25*, 1363–1375. [CrossRef]

3. Song, B.; Shi, H.; Wang, M.; Gu, R. The research on the effect of Digital Economy Development on Urban Air Quality. *Front. Environ. Sci.* **2022**, *10*, 993353. [CrossRef]
4. Çitil, M.; İlbasmış, M.; Olanrewaju, V.O.; Barut, A.; Karaoğlan, S.; Ali, M. Does Green Finance and institutional quality play an important role in air quality. *Environ. Sci. Pollut. Res.* **2023**, *30*, 53962–53976. [CrossRef] [PubMed]
5. Bakhsh, S.; Yin, H.; Shabir, M. Foreign Investment and CO_2 emissions: Do Technological Innovation and Institutional Quality matter? Evidence from system GMM approach. *Environ. Sci. Pollut. Res.* **2021**, *28*, 19424–19438. [CrossRef] [PubMed]
6. Borck, R.; Schrauth, P. Population density and Urban Air Quality. *Reg. Sci. Urban Econ.* **2021**, *86*, 103596. [CrossRef]
7. Roy, A.; Acharya, P. Energy inequality and Air Pollution Nexus in India. *Sci. Total Environ.* **2023**, *876*, 162805. [CrossRef] [PubMed]
8. Rentschler, J.; Leonova, N. Global air pollution exposure and poverty. *Nat. Commun.* **2023**, *14*, 4432. [CrossRef] [PubMed]
9. Farzanegan, M.R.; Gholipour, H.F.; Javadian, M. Air pollution and internal migration: Evidence from an iranian household survey. *Empir. Econ.* **2022**, *64*, 223–247. [CrossRef]
10. Huang, Z.; Zheng, W.; Tan, X.; Zhang, X.; Liu, L. Polluted air increases perceived corruption. *J. Pac. Rim Psychol.* **2016**, *10*, e13. [CrossRef]
11. Herrnstadt, E.; Heyes, A.; Muehlegger, E.; Saberian, S. Air pollution and criminal activity: Microgeographic evidence from Chicago. *Am. Econ. J. Appl. Econ.* **2021**, *13*, 70–100. [CrossRef]
12. Tran, N.H.; Fu, L.; Boehe, D.M. How does urban air pollution affect corporate environmental performance? *J. Clean. Prod.* **2023**, *383*, 135443. [CrossRef]
13. Li, X.; Yang, Y. The relationship between air pollution and company risk-taking: The moderating role of Digital Finance. *Front. Environ. Sci.* **2022**, *10*, 988450. [CrossRef]
14. Ju, H.L.; Wen, H. Air Pollution, Ecological Transformation and Heterogeneity of Brain Drain. *Hum. Resour. Dev. China* **2021**, *9*, 90–109. [CrossRef]
15. Zhang, A.; Wang, S.; Liu, B. How to control air pollution with economic means? Exploration of China's Green Finance Policy. *J. Clean. Prod.* **2022**, *353*, 131664. [CrossRef]
16. Kuklinska, K.; Wolska, L.; Namiesnik, J. Air Quality Policy in the U.S. and the EU—A Review. *Atmos. Pollut. Res.* **2015**, *6*, 129–137. [CrossRef]
17. Sun, C.; Xu, S.; Yang, M.; Gong, X. Urban Traffic Regulation and air pollution: A case study of urban motor vehicle restriction policy. *Energy Policy* **2022**, *163*, 112819. [CrossRef]
18. Kong, H.; Jin, S.T.; Sui, D.Z. Can transportation network companies improve urban air quality? *Transp. Res. Part D Transp. Environ.* **2023**, *119*, 103767. [CrossRef]
19. Feng, Y.; Chen, H.; Chen, Z.; Wang, Y.; Wei, W. Has environmental information disclosure eased the economic inhibition of air pollution? *J. Clean. Prod.* **2021**, *284*, 125412. [CrossRef]
20. Aram, S.A.; Nketiah, E.A.; Saalidong, B.M.; Wang, H.; Afitiri, A.R.; Akoto, A.B.; Lartey, P.O. Machine learning-based prediction of Air Quality Index and Air Quality Grade: A comparative analysis. *Int. J. Environ. Sci. Technol.* **2023**, *21*, 1345–1360. [CrossRef]
21. Li, W.; Zhang, K. Does air pollution crowd out foreign direct investment inflows? Evidence from a quasi-natural experiment in China. *Environ. Resour. Econ.* **2019**, *73*, 1387–1414. [CrossRef]
22. Li, B.; Shi, S.; Zeng, Y. The impact of haze pollution on firm-level TFP in China: Test of a mediation model of labor productivity. *Sustainability* **2020**, *12*, 8446. [CrossRef]
23. Cao, Y.; Wang, Q.; Zhou, D. Does air pollution inhibit manufacturing productivity in Yangtze River Delta, China? Moderating effects of temperature. *J. Environ. Manag.* **2022**, *306*, 114492. [CrossRef] [PubMed]
24. Le, D.; Li, Y.; Ren, F. Does air quality improvement promote enterprise productivity increase? based on the spatial spillover effect of 242 cities in China. *Front. Public Health* **2022**, *10*, 1050971. [CrossRef] [PubMed]
25. Liu, S.; Yang, Y.; Cai, L. Impact of air quality on enterprise productivity: Evidence from Chinese listed companies. *Front. Environ. Sci.* **2023**, *10*, 1095393. [CrossRef]
26. Zivin, J.G.; Neidell, M. The impact of pollution on worker productivity. *Am. Econ. Rev.* **2012**, *102*, 3652–3673. [CrossRef] [PubMed]
27. Xue, S.; Zhang, B.; Zhao, X. Brain drain: The impact of air pollution on firm performance. *J. Environ. Econ. Manag.* **2021**, *110*, 102546. [CrossRef]
28. Farooq, U.; Ashfaq, K.; Rustamovna, R.D.; Al-Naimi, A.A. Impact of air pollution on Corporate Investment: New Empirical Evidence from BRICS. *Borsa Istanb. Rev.* **2023**, *23*, 876–886. [CrossRef]
29. Canha, N.; Justino, A.R.; Gamelas, C.A.; Almeida, S.M. Citizens' perception on air quality in Portugal—How concern motivates awareness. *Int. J. Environ. Res. Public Health* **2022**, *19*, 12760. [CrossRef]
30. Schmitz, S.; Weiand, L.; Becker, S.; Niehoff, N.; Schwartzbach, F.; von Schneidemesser, E. An assessment of perceptions of air quality surrounding the implementation of a traffic-reduction measure in a local urban environment. *Sustain. Cities Soc.* **2018**, *41*, 525–537. [CrossRef]
31. Wang, J.; Tang, D. Air Pollution, Environmental Protection Tax and well-being. *Int. J. Environ. Res. Public Health* **2023**, *20*, 2599. [CrossRef] [PubMed]
32. Yang, X.; Dong, X.; Jiang, Q.; Liu, G. Factors influencing public concern about environmental protection: An analysis from China. *Discret. Dyn. Nat. Soc.* **2019**, *2019*, 5983160. [CrossRef]
33. Du, W.; Li, M.; Fan, Y.; Liang, S. Can public environmental concern inhibit the market entry of polluting firms: Micro Evidence from China. *Ecol. Indic.* **2023**, *154*, 110528. [CrossRef]

34. He, X.; Shi, J. The effect of air pollution on Chinese Green Bond Market: The mediation role of public concern. *J. Environ. Manag.* **2023**, *325*, 116522. [CrossRef] [PubMed]
35. Zhang, X.; Tan, J.; Chan, K.C. Air pollution and initial public offering underpricing. *Appl. Econ.* **2021**, *53*, 4582–4595. [CrossRef]
36. Shen, Y.; Lyu, M.; Zhu, J. Air pollution and corporate green financial constraints: Evidence from China's listed companies. *Int. J. Environ. Res. Public Health* **2022**, *19*, 15034. [CrossRef] [PubMed]
37. Viet, H.N.; Quynh, H.H.; Trung, T.T. Impact of financial constraints on the development of Vietnam's firms. *Manag. Sci. Lett.* **2020**, *10*, 1683–1692. [CrossRef]
38. Tan, Z.; Yan, L. Does Air Pollution Impede Corporate Innovation? *Int. Rev. Econ. Financ.* **2021**, *76*, 937–951. [CrossRef]
39. Xu, S.C.; Meng, X.N.; Wang, H.N.; Zhang, J.N.; Feng, C. The costs of air pollution: How does air pollution affect technological innovation? *Environ. Dev. Sustain.* 2024. [CrossRef]
40. Chen, Z.; Hao, X.; Zhou, M. Does institutional quality affect air pollution? *Environ. Sci. Pollut. Res.* **2022**, *29*, 28317–28338. [CrossRef]
41. Lee, J.W.; Lee, Y.H. Effects of environmental regulations on the total factor productivity in Korea from 2006–2014. *Asian J. Technol. Innov.* **2020**, *30*, 68–89. [CrossRef]
42. Wang, Q.; Ren, S.; Hou, Y. Atmospheric Environmental Regulation and industrial total factor productivity: The mediating effect of capital intensity. *Environ. Sci. Pollut. Res.* **2020**, *27*, 33112–33126. [CrossRef] [PubMed]
43. Yang, M.; Xu, J.; Yang, F.; Duan, H. Environmental regulation induces technological change and green transformation in Chinese cities. *Reg. Environ. Chang.* **2021**, *21*, 41. [CrossRef]
44. Taglialatela, J.; Pirazzi Maffiola, K.; Barontini, R.; Testa, F. Board of directors' characteristics and environmental sdgs adoption: An international study. *Corp. Soc. Responsib. Environ. Manag.* **2023**, *30*, 2490–2506. [CrossRef]
45. Rahman, H.U.; Zahid, M.; Jan, A.; Al-Faryan, M.A.; Hussainey, K. Is it the mere female directors or their attributes that matter for the quality of corporate sustainability disclosures? *Bus. Strategy Environ.* **2023**, *33*, 661–678. [CrossRef]
46. Hu, L.; Yang, D. Female Board Directors and Corporate Environmental Investment: A contingent view. *Sustainability* **2021**, *13*, 1975. [CrossRef]
47. Cosma, S.; Schwizer, P.; Nobile, L.; Leopizzi, R. Environmental attitude in the board. who are the "green directors"? evidences from Italy. *Bus. Strategy Environ.* **2021**, *30*, 3360–3375. [CrossRef]
48. Lu, X.D.; Lian, Y.J. Estimation of Total Factor Productivity of Industrial Enterprises in China: 1999–2007. *China Econ. Q.* **2012**, *11*, 179–196. [CrossRef]
49. Benchrif, A.; Wheida, A.; Tahri, M.; Shubbar, R.M.; Biswas, B. Air quality during three COVID-19 lockdown phases: AQI, PM2.5 and NO_2 assessment in cities with more than 1 million inhabitants. *Sustain. Cities Soc.* **2021**, *74*, 103170. [CrossRef]
50. Wu, B.; Fang, H.; Jacoby, G.; Li, G.; Wu, Z. Environmental regulations and innovation for sustainability? Moderating effect of political connections. *Emerg. Mark. Rev.* **2022**, *50*, 100835. [CrossRef]
51. Ren, X.; Ren, Y. Public environmental concern and corporate ESG performance. *Financ. Res. Lett.* **2024**, *61*, 104991. [CrossRef]
52. Cattaneo, M.D.; Jansson, M.; Ma, X. Manipulation testing based on density discontinuity. *Stata J. Promot. Commun. Stat. Stata* **2018**, *18*, 234–261. [CrossRef]
53. Li, H.B.; Fu, Y.; Zhang, J.X.; He, Y.; Pu, W.Y.; Xia, W.; Zhao, F.S.; Zhou, D.P.; Zhang, D.G. Precipitation Characteristics and Correlation Analysis During an Air Pollution Episode. *Meteorol. Mon.* **2018**, *44*, 655–664. [CrossRef]
54. Sager, L. Estimating the effect of air pollution on road safety using atmospheric temperature inversions. *J. Environ. Econ. Manag.* **2019**, *98*, 102250. [CrossRef]
55. Zhu, C.; Lee, C.C. The internal and external effects of air pollution on innovation in China. *Environ. Sci. Pollut. Res.* **2020**, *28*, 9462–9474. [CrossRef]
56. Zhai, X.; An, Y. Analyzing influencing factors of green transformation in China's manufacturing industry under Environmental Regulation: A structural equation model. *J. Clean. Prod.* **2020**, *251*, 119760. [CrossRef]
57. Ding, X.; Ye, L.; Yang, Y.; Efifimova, O.; Steblyanskaya, A.; Zhang, J. The Impact Mechanism of Environmental Information Disclosure on Corporate Sustainability Performance—Micro-Evidence from China. *Sustainability* **2022**, *14*, 12366. [CrossRef]
58. Ding, X.; Jing, R.; Wu, K.; Petrovskaya, M.; Li, Z.; Steblyanskaya, A.; Ye, L.; Wang, X.; Makarov, V. The Impact Mechanism of Green Credit Policy on the Sustainability Performance of Heavily Polluting Enterprises—Based on the Perspectives of Technological Innovation Level and Credit Resource Allocation. *Int. J. Environ. Res. Public Health* **2022**, *19*, 14518. [CrossRef] [PubMed]
59. Wang, C.; Nie, P.Y.; Peng, D.H.; Li, Z.H. Green insurance subsidy for promoting clean production innovation. *J. Clean. Prod.* **2017**, *148*, 111–117. [CrossRef]
60. Pu, C.; Mo, C.; Li, P. Green insurance, technology insurance, and corporate green innovation. *Front. Environ. Econ.* **2024**, *2*, 1266745. [CrossRef]
61. Wang, Y.; Lu, T.; Qiao, Y. The effect of air pollution on corporate social responsibility performance in high energy-consumption industry: Evidence from Chinese listed companies. *J. Clean. Prod.* **2021**, *280*, 124345. [CrossRef]
62. Huang, Q.Y.; Yao, Q.; Huang, X.S.; Wang, B. Economic Policy Uncertainty and Corporate Investment Convergence Behavior. *South China J. Econ.* **2021**, *5*, 69–90. [CrossRef]