sustainability

MDPI

Article

Air Quality Monitoring and Total Factor Productivity of Polluting Firms in China

Xiao Liu [1], Lingyan He [2], Jianfei He [3] and Rongxi Zhou [3,*]

[1] School of Economics and Management, North China University of Technology, Beijing 100144, China; liuxiao2022@ncut.edu.cn
[2] Department of Economics, Party School of Nanjing Municipal Committee of CPC, Nanjing 210046, China; 201800210064@uibe.edu.cn
[3] China School of Banking and Finance, University of International Business and Economics, Beijing 100029, China; 202300220057@uibe.edu.cn
* Correspondence: zhourx@uibe.edu.cn; Tel.: +86-10-6449-3082

Abstract: In recent decades, sustainable development and environmental protection, especially air quality, have become key concerns for governments as well as scholars. As a typical regulation for air quality monitoring, the Ambient Air Quality Standard (AAQS) (2012) is a good attempt at balancing economic growth and environmental protection in development exploration. Therefore, this paper takes the AAQS (2012) as a quasi-natural experiment to detect its influence on the total factor productivity (TFP) of polluting firms. The results of a DID model suggest that the AAQS (2012) significantly improves the TFP of polluting firms in China even after several robust tests. Further, this paper also finds that firms in high urbanization and with over-investment experience are more sensitive to the new standard. As for the channels, the results show that air quality monitoring affects firms' TFP by adjusting the industry concentration level and innovation capabilities. This research offers a novel perspective for decision-makers, highlighting the importance of harmonizing economic growth with environmental sustainability.

Keywords: environmental regulation; air quality; total factor productivity (TFP); high urbanization; over-investment

check for updates

Citation: Liu, X.; He, L.; He, J.; Zhou, R. Air Quality Monitoring and Total Factor Productivity of Polluting Firms in China. *Sustainability* **2024**, *16*, 6785. https://doi.org/10.3390/su16166785

Academic Editors: Roberto Cervelló-Royo, Marta García-Mollá and Rosa Puertas

Received: 11 July 2024
Revised: 4 August 2024
Accepted: 5 August 2024
Published: 7 August 2024

Copyright: © 2024 by the authors. Licensee MDPI, Basel, Switzerland. This article is an open access article distributed under the terms and conditions of the Creative Commons Attribution (CC BY) license (https://creativecommons.org/licenses/by/4.0/).

1. Introduction

In the past few decades, China's tremendous development has brought about environmental pollution problems and caused enormous pressure on the ecological environment [1]. In 2019, the data from the 2019 Bulletin on China's Ecological Environment issued by the Ministry of Ecological Environment of the People's Republic of China showed that nearly half of 338 main cities reported they had experienced air pollution, and 188 cities reported serious pollution for a cumulated 1666 days. This figure is an increase of 88 days compared with that in 2018. China has experienced rapid economic growth in the past few decades and has achieved continuous growth, thus becoming the world's second-largest economy. But it should be noted that the rapid development of the economy has also brought about environmental degradation. One of the issues is air pollution, which brings a negative impact on China's international reputation and the pursuit of high-quality economic growth [2]. Governments and scholars are paying growing attention to air pollution with a particular emphasis on fine particulate (PM2.5) pollution [3], productivity [4,5], and economic growth [6]. Developed countries and some international organizations have conducted systematic and effective research on ambient air quality monitoring and the formulation of air quality standards. They proposed a series of Ambient Air Quality Standards, and accumulated rich experience [7,8]. The adoption of benchmarks by the United States and Switzerland is a typical representative of Ambient Air Quality Standard setting methods in various countries around the world [9].

Recently, China has continued to strengthen ecological and environmental protection by launching laws and regulations [10]. The government proposes the target of continuously improving environmental quality and strengthening multi-pollutant collaborative monitoring. The first air quality standard was implemented in 1982 and revised in 1996 and 2000. However, this standard played a lesser role in influencing ambient air quality. In 2012, the Ambient Air Quality Standard was substantially rewritten and implemented in batches throughout the country. There are two main special changes in the latest revision. One change is the proposal of monitoring PM2.5. Another is the focus of environmental management shifting from environmental pollution control to environmental quality improvement. The Ambient Air Quality Standard (AAQS) (2012) [11] has been regarded as a milestone in air quality monitoring. The formulation and revision of Chinese Ambient Air Quality Standards are based on scientific evidence, drawing on the experience of developed countries and adapting to the national conditions and development stages.

The Chinese government has introduced multiple policies, committed to upgrading from high-speed growth to high-quality development. The AAQS (2012) is an air pollution control standard policy with certain research value in the current stage of improving air quality in China. Polluting firms are the main actors in air pollution prevention and control policies. Compared with other economic indicators, total factor productivity (TFP) can effectively measure changes in the technological level of firms and intuitively reflect adjustments in production activities. This means that TFP can better reflect the quality level of economic development. As an air pollution control policy, whether the AAQS (2012) can improve the total factor productivity of firms and achieve a win–win in the sustainable development of the economy and environment is a question that needs to be proved. Studying the specific impact of air quality standard policies on firms' productivity can provide management strategies for companies. Further testing the mechanism path of policy implementation effectiveness can help the government face its own governance effectiveness and improve policies.

TFP reflects the additional output achieved through technological progress and efficiency improvement in addition to capital and labor inputs and is an important indicator to measure the quality of economic development [12,13]. TFP growth is one of the key ways to affect economic growth [14]. TFP stands as a pivotal metric in gauging the quality and efficiency of firms in important documents such as the "Demand-Based Reflection, Quality Improvement, Efficiency Improvement, Transformation and Upgrading Statistical Indicator System" issued by the National Bureau of Statistics of China on September 9, 2014, and the "13th Five Year Plan for Shanghai's Manufacturing Industry Transformation and Upgrading" issued by Shanghai on 30 June 2016.

Firms are affected by environmental regulation policies on technological innovation [15] and structural transformation [16] in the production and operation process, which further affects TFP. From one side, environmental regulation can not only reduce the pollution emission of firms but also improve the TFP by promoting technological innovation and the rectification of management processes. These enable firms to achieve a win–win situation of both environmental and productivity benefits [17]. Looking from the other side, the implementation of cleaner production generates extra costs, which increases the general expenditure of production and operation, thus reducing the TFP [18]. In addition, environmental regulation and productivity are intricately linked through a complex nonlinear relationship, often exemplified by a U-shaped pattern [19]. It is still under study as to whether air quality monitoring can improve the TFP of firms to achieve the win–win goal of economic and environmental development [20,21].

Examining the influence of air pollution control policies on firms' TFP is crucial for the pursuit of high-quality economic growth. There have been some studies exploring the impact of environmental regulations on the TFP of firms. Most of this research posits that environmental regulations serve as a bulwark against ecological degradation, enhancing environmental quality and fostering the sustainable progression of the manufacturing industry. However, the consensus on these outcomes remains contentious, particularly concerning the

reactions of firms to air quality monitoring. Furthermore, there is a divergence in the scholarly community regarding the precise mechanisms by which environmental regulations influence production efficiency, and little has been achieved regarding the transmission role of industry concentration and enterprise innovation dimensions, as well as comparing the differences in impact of urbanization level and enterprise investment level.

To address the effect of air quality monitoring, this paper selects the AAQS (2012) of China as the quasi-natural experiment and uses the difference-in-differences (DID) method to examine the impact of air quality control policy on the TFP of firms. Furthermore, to avoid possible endogenous problems, a series of robust tests are carried out, including a parallel trend test, a placebo test, the PSM-DID method, and the replacement of proxies, and the results are consistent. To explore this channel, the path of how air pollution control policy affects the TFP of firms is further investigated. The analysis of heterogeneity encompasses a broader and more integrated perspective, ensuring a examination of the factors involved. The main results are as follows: air quality monitoring promotes enterprise TFP. The mechanisms are industry concentration and firm innovation capabilities. The promotion effect is more significant for over-investment firms and enterprises in high-urbanization areas.

This paper delivers a significant contribution to the literature from the following two aspects: First, in examining the impact of the AAQS (2012) on the TFP of polluting firms, this paper eliminates possible endogenous problems through the DID method and further expands the literature on the relationship between air quality monitoring and enterprise productivity. This paper expands research on the impact mechanism of air quality monitoring and investigates the path of how the air pollution control policy affects the TFP of firms based on the industry concentration level and firm innovation capability. Second, the existing literature takes major developed economies as the research object. This paper takes China as an example to systematically study the impact of environmental policies on TFP in the transition economy, such as the effect differences between cities with different levels of urbanization and firms with different levels of investment experience.

The remainder of this paper is organized as follows: Section 2 reviews the literature and proposes the hypotheses. The empirical methodology is explained in Section 3. Results are in Section 4. Section 5 conducts channel analysis and heterogeneity analysis. Section 6 provides discussions of the findings and the innovative aspects. Section 7 concludes the key points of this paper.

2. Literate Review and Hypothesis Development

2.1. Environmental Regulation and Total Factor Productivity

There are different views on the impact of environmental regulation on firms' TFP [22]. Some academics hold the point that environmental regulation has a positive impact on firms' TFP. Porter's hypothesis puts forward that appropriate environmental regulation can promote firms' innovation and improve firms' productivity and profitability, thus helping to improve firms' TFP [23]. Through an empirical study of a manufacturing industry sample, Hamamoto found that environmental regulation stimulates the growth of R&D investment and has a positive effect on the growth of TFP [24]. Testa et al. used a sample of construction industry objects in three EU regions in the first half of 2009 and found that stricter environmental regulation and well-designed "direct supervision" increase firms' investment in technological innovation and improve firms' business performance [25]. Granderson and Prior studied the "Clean Air Act" promulgated by the United States in 1990 and found that the implementation of the first phase of the act increases the cost and TFP of firms in the power industry [26]. Rubashkina et al. found that the TFP of the European manufacturing industry would be promoted by applying environmental regulation [27]. Liu et al. investigated whether the national green industry policy can play an important role in the transformation and upgrading of enterprise structure, thereby improving production efficiency [28]. Their research found that the green industrial policy improves the resource allocation ability and TFP growth of firms. The main paths of policy

influence on TFP are through the compensation channel to encourage firms' innovation and the market channel to eliminate unqualified firms. Li et al. explored the relationship between environmental regulation and firms' TFP. Based on the firm-level data from 2000 to 2007, they showed that the environment assessment policy for the Huai River Basin implemented in 2004 significantly improved the firm TFP in the next three years [29]. Xie et al. developed a partial-equilibrium model that integrates the selection of optimal compliance strategies, thereby theoretically elucidating the intricate relationship between environmental regulations and TFP [30].

Some other research puts forward different ideas that firms transfer limited resources from productive inputs to environmental protection activities to meet environmental regulations. The decreased expenses in the production factors such as labor and capital negatively impact the firm's TFP [31]. Lanoie et al. studied the Quebec manufacturing sector in Canada and found that in the short term, the increase in environmental regulation intensity causes additional costs to firms, resulting in a negative impact on TFP [19]. Broberg et al. conducted a study based on Swedish manufacturing data to measure environmental regulation. Empirical evidence demonstrates that regulation application reduced TFP in the pulp and paper industry [32]. Empirical studies of Canadian manufacturing firms corroborate the adverse impacts of environmental regulations, as documented by Wang and colleagues [33]. In China, while environmental regulations are known to foster innovation, there is scant evidence to suggest that they bolster the competitiveness of firms. Moreover, a concerning trend is the potential for such regulations to expedite the demise of firms, as highlighted by Habermann and Fischer [34]. Furthermore, the phenomenon of highly polluting enterprises migrating to jurisdictions with more lenient regulations to evade oversight is not uncommon. However, as these areas witness an intensification of environmental oversight, these enterprises, in turn, face heightened risks of insolvency.

Most existing studies focused on developed economies, while it is also necessary to pay attention to developing economies with transforming market structures. As an example, China used relatively low labor and land costs and other input factors in the early stage of development to enable firms to achieve production expansion, thus boosting China's proportion of the global manufacturing output. With a global landscape characterized by uncertainty and risks, spanning the recent COVID-19 pandemic, international trade conflicts, global warming issues, rapid developments in new technology, and changing world order, developing countries are facing greater pressure in terms of industrial structure adjustment and pollution control than ever. Some studies have noticed the impact of environmental regulation on TFP in the context of developing countries and found a positive relationship between environmental regulations and firms' TFP [35–38].

Air quality monitoring, as an essential component of environmental regulation, is an indispensable part of modern society's environmental protection and sustainable development strategy. By regularly or continuously measuring the concentrations of various pollutants in the atmosphere, it assesses the state of air quality, provides a scientific basis for environmental management decisions, and thus promotes the improvement of environmental quality and the protection of public health. The agreement on these results is still a matter of debate, especially regarding the ways in which firms react to air quality monitoring. Based on the above discussion, we propose our first hypothesis:

H1. *Air quality monitoring significantly improves the total factor productivity of polluting firms.*

2.2. Related Research on Air Quality Monitoring

Although the air quality standard has existed for years, the discussion mainly focuses on the established framework for standard setting, comparative analysis of the pertinent contents, and evaluation of the benefits. Owens et al. discussed the methodology and causal framework for evaluating the comprehensive scientific assessment (ISA) developed by the U.S. Environmental Protection Agency (EPA) [39]. Wang et al. used the DID model to appraise the efficacy of the new Ambient Air Quality Standard on the environment [40].

The results showed that the new standard reduces PM2.5 and SO_2 emissions in pilot cities in both the short and long term. Ma et al. used the adjusted human capital method and life value statistics and found that the implementation of the new standard impacts human health by reducing the exposure to air pollution and increasing the marginal income of public health [41].

There are also studies focused on the impact of air pollution. Liu et al. examined the empirical costs of air pollution under micro-institutional conditions in China [42]. The results indicated a negative correlation between the quality of internal controls and air pollution, which has also been affected by the environment, ownership structure, and leader's demographic characteristics. Li et al. conducted an empirical test based on the air quality data released by the China National Environmental Monitoring Center and used the listed firms from 2013 to 2017 as the sample, and found that haze pollution has a direct negative impact on TFP by reducing labor productivity [43]. Chen et al. found that atmospheric quality monitoring policy can improve eco-efficiency, promoting sustainable urban development [44].

Most existing studies focus on the content of Ambient Air Quality Standards, but few pay attention to the effect of standards on productivity, especially from the micro firm's TFP point of view. Combined with the target of curbing environmental pollution, the impact of the policy on polluting firms seems to be very important. As mentioned before, developing countries are experiencing great changes in development models, which also provides a research perspective different from developed countries for empirical research. Arrow et al. pointed out that there is an interactive relationship between urbanization and air pollution [45]. Luo et al. used urban-level panel data for empirical analysis and concluded that the improvement of urbanization level can inhibit air pollution [46].

However, there is no research that focuses on whether the effect of environmental regulation on firms' TFP can change with the urbanization process of the located cities. The AAQS (2012) indeed represents a significant milestone in China's field of air quality monitoring. The introduction of these standards signifies a solid step forward for China in environmental protection and the improvement of air quality. Based on this, this paper takes the AAQS (2012) as the policy shock to examine the impact of air pollution control policies on the TFP of polluting firms in different urbanization cities. According to this discussion, we posit our second hypothesis:

H2. *Air quality monitoring significantly improves the total factor productivity of polluting firms located in areas with a higher degree of regional urbanization.*

Before the implementation of new air quality monitoring, due to the preference of local governments, over-investment was regarded as one of the setbacks to the strict implementation of environmental regulation in China. Local governments make polluting firms easier to obtain credit from local financial institutions, so as to expand production capacity, which eventually leads to over-investment performance. Although over-investment violates the principle of maximizing shareholder value, company managers and local officials would benefit from it [47]. This phenomenon has already been found in the existing literature [48,49].

In some cases, when the production technology shows economies of scale, excess capacity allows the company to achieve lower production costs, thus increasing sales and regional GDP. However, with continuous attention to environmental protection, the implementation of new environmental regulations reduces the intervention of local officials, and firms with over-investment behavior receive more suspension and investigation [47]. Since over-invested firms are under greater pressure of investigation, they tend to be more sensitive to the launch of new air quality monitoring, and thus their TFP is more significantly affected. We therefore posit our third hypothesis:

H3. *Air quality monitoring significantly improves the total factor productivity of over-investment polluting firms.*

3. Data and Methodology

3.1. Sample and Data

This study used Chinese polluting firm data from the Shanghai and Shenzhen stock exchanges and captured data from China's stock market and accounting research (CSMAR) data venture from 2007 to 2020. Polluting firms are characterized by the Directory of Classified Management of Environmental Protection Inspection of Listed Firms. This paper selected 2007 as the start year because firms started to publish environmental investments according to accounting system reform from this year. The data of firms with missing values were omitted from the sample, which led to a final useable sample of 7964 firm-year observations. Table 1 illustrates the distribution of the research sample industry. An analysis of Table 1 elucidates that the major industries involved in this research are manufacturing (78.21%), electricity, heat, gas, and water production and supply (9.94%) and mining (7.82%).

Table 1. Sample distribution.

Industry	% of Sample
Manufacturing	78.21
Electricity, heat, gas, and water production and supply	9.94
Mining	7.82
Construction	2.22
Real estate	0.43
Transportation, storage, and postal services	0.27
Accommodation and catering	0.21
Wholesale and retail	0.19
Comprehensive	0.14
Others	0.57

The implementation of AAQS (2012) is an objective requirement for strengthening atmospheric environmental governance in the new era. The Ministry of Environmental Protection has issued the Implementation Plan for the First Phase Monitoring of the New Air Quality Standard, requiring all regions to implement the new standard policies in stages. The regions with good economic and technological foundations and prominent composite air pollution have implemented new standard policies since 2012, including key regions such as Beijing–Tianjin–Hebei, the Yangtze River Delta, and the Pearl River Delta, as well as municipalities and provincial capital cities, totaling 74 cities. This policy added air quality measurement indicators such as PM2.5 and O_3 to the original policy, and the air quality data of 74 pilot cities were unified and comprehensively disclosed to the public, higher-level governments, and news media from 1 January 2013.

Specifically, AAQS (2012) contains 74 pilot cities, including 13 cities in Beijing–Tianjin–Hebei and surrounding areas, 26 cities in the Yangtze River Delta urban agglomeration, 9 cities in the Pearl River Delta urban agglomeration, and provincial capitals. Table 2 reports these cities and Figure 1 shows the location of the pilot city.

Table 2. Composition of pilot cities.

Area	Cities
Beijing–Tianjin–Hebei and surrounding areas (13 cities)	Beijing, Tianjin, Shijiazhuang, Tangshan, Baoding, Qinhuangdao, Langfang, Cangzhou, Chengde, Zhangjiakou, Handan, Xingtai, Hengshui
Yangtze River Delta urban agglomeration (26 cities)	Shanghai, Nanjing, Wuxi, Changzhou, Suzhou, Nantong, Yancheng, Yangzhou, Zhenjiang, Taizhou, Hangzhou, Ningbo, Jiaxing, Huzhou, Shaoxing, Jinhua, Zhoushan, Taizhou, Hefei, Wuhu, Maanshan, Tongling, Anqing, Chuzhou, Chizhou, Xuancheng
Pearl River Delta urban agglomeration (9 cities)	Guangzhou, Shenzhen, Zhuhai, Dongguan, Foshan, Zhongshan, Huizhou, Jiangmen, Zhaoqing
Other municipalities directly under the central government and provincial capitals, etc. (26 cities)	Chongqing, Taiyuan, Xian, Jinan, Zhengzhou, Changchun, Haerbin, Nanchang, Fuzhou, Wuhan, Changsha, Chengdu, Guiyang, Kunming, Haikou, Lanzhou, Xining, Hohhot, Urumqi, Lhasa, Nanning, Yinchuan, Shenyang, Xiamen, Dalian, Qingdao

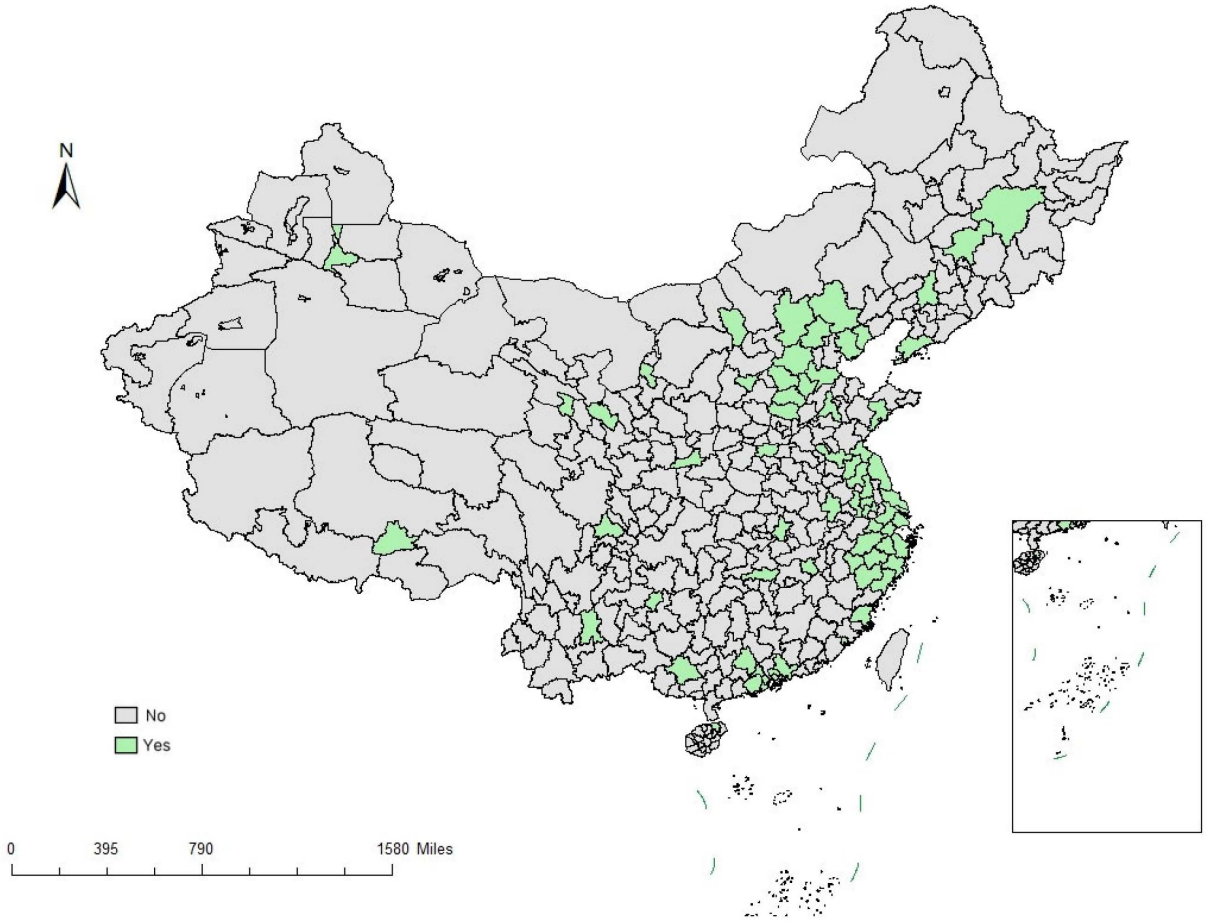


Figure 1. The location of the pilot city.

3.2. Variable Selection

3.2.1. Dependent Variable

This paper uses consistent semiparametric estimation (OP method) followed by Olley and Pakes to estimate the dependent variable, TFP [50]. We set the production function first. The Cobb–Douglas production function (C-D production function) has been widely used with the benefit of more information being contained, as well as it being intuitive and consistent with common sense. The standard form of the C-D production function is typically expressed as follows:

$$Y_{it} = A_{it} L_{it}^{\alpha} K_{it}^{\beta} \tag{1}$$

where Y_{it} is output and L_{it} and K_{it} reflect labor and capital input, respectively. A_{it} is commonly referred to as TFP. Equation (1) can be transformed into a linear format by taking its logarithm:

$$\ln Y_{it} = \alpha \ln L_{it} + \beta \ln K_{it} + \mu_{it} \tag{2}$$

Equation (2)'s residual term encompasses the logarithmic expression of firms' TFP, denoted as A_{it}. Generally, the estimated value of TFP can be obtained by estimating Equation (2). However, there are inevitable technical problems when estimating with measurement methods, that is, simultaneity deviation and sample selectivity deviation. One of the most prominent is the simultaneity deviation problem. During the actual production process, a portion of a firm's efficiency is observable in the current period. According to the principle of maximum production, the firms' decision-maker can immediately adjust the input com-

bination of production factors according to this information. In order to solve this problem, the residual of Equation (2) can be expressed in the subsequent form:

$$\ln Y_{it} = \alpha \ln L_{it} + \beta \ln K_{it} + \overline{\omega}_{it} + e_{it} \tag{3}$$

where $\overline{\omega}_{it}$ is a part of the residual term, which can be observed by firms and affect the selection of current factors. e_{it} is a real residual term, including unobservable technical shock and measurement error. The OP approach posits that companies base their investment choices on their current productivity levels. The firms' current investments serve as a surrogate for the unobservable effects of productivity. Additionally, it is essential to address the issue of simultaneity bias in the analysis.

The production function is expressed as

$$Y_{it} = A_{it} L_{it}^{\alpha} K_{it}^{\beta} \tag{4}$$

where Y_{it} is the output of firm i in year t. Given the presence of solid data, this paper uses the year-end operating revenue as the firm output. A_{it} is commonly referred to as the total factor productivity (TFP). K_{it} and L_{it} represent the fixed assets and employee scale of the firms, respectively.

By applying the logarithmic transformation to Equation (4), it can be reconfigured into the subsequent linear format:

$$\ln Y_{it} = \alpha \ln L_{it} + \beta \ln K_{it} + \mu_{it} \tag{5}$$

The residual component μ_{it} in Equation (5) encompasses information on the logarithm form of the firm's TFP.

In this scenario, if the error term is indicative of TFP, then its observable component can exert an influence on the selection of factor inputs. This means that the residual term is correlated with the regression term, resulting in potential bias within the estimation results of TFP. To address this issue, the residuals from Equation (5) can be dissected as follows:

$$\ln Y_{it} = \alpha \ln L_{it} + \beta \ln K_{it} + \overline{\omega}_{it} + e_{it} \tag{6}$$

Among them, $\overline{\omega}_{it}$ is a part of the residual term that can be observed by enterprises and affect their current factor choices. e_{it} is the true residual term, encompassing unobservable technological shocks and measurement errors. The above issues have been addressed through various methods, leading to multiple estimation methods for TFP. Specifically, the TFP estimation is based on the following model:

$$\ln Y_{it} = \beta_0 + \beta_k \ln K_{it} + \beta_t \ln L_{it} + \varepsilon_{it} \tag{7}$$

Generally, the estimated value of TFP can be obtained by estimating Equation (7), and the error term ε_{it} represents TFP.

3.2.2. Independent Variable

In our model, the interaction term *Treat* × *Post* serves as the independent variable. The experimental group in this paper, which is measured by the dummy variable *Treat*, refers to 74 pilot cities, and the experimental period, which is represented by the dummy variable *Post*, is 2012 onwards. The interaction variable, denoted as *Treat* × *Post*, is assigned a value of 1 when firm i is part of the experimental group and during the period of the experiment. In all other cases, it is set to 0. The variable *Treat* captures the distinctions between the experimental and control groups, while *Post* delineates the changes in firm i from before to after the experiment. The interaction term *Treat* × *Post*, *therefore*, encapsulates the effects of the policy intervention.

3.2.3. Control Variables

Firm size, firm age, firm leverage, firm performance, firm employees, firm ownership, board independence, and analyst following, which may have an effect on firms' TFP, are selected as control variables. The firm size (*Size*) is measured by the natural logarithm of total assets (in millions of RMB). Firm age (*Age*) is measured by the natural logarithm of listed years. Following Francoeur et al., this paper selects the ratio of total debt to total assets to represent firm leverage (*Lev*), and the sales growth rate (*Growth*) is used to measure firm performance [51]. Firm employees (*Labor*) are measured by the natural logarithm of total employees. Firm ownership (*State*) is measured by a dummy variable, which equals 1 for firms with state ownership (including state-owned shares and state-owned legal person shares) and 0 otherwise. The ratio of the independent director scale to the total director scale is used to measure board independence (*Board*). As for analyst following (*Analyst*), we use the natural logarithm of total analyst reports in a certain year to represent this. Moreover, to control for possible variable effects across industries and regions, this research also includes industry dummies and province dummies.

The variables selected in this study are consolidated and presented in Table 3.

Table 3. Variable definition.

Variables	Definition
TFP	Total factor productivity.
Treat	1 if firm *i* is located in one of 74 pilot cities and 0 otherwise.
Post	1 if year *t* is 2012 onwards and 0 otherwise.
Size	Natural logarithm of total assets of firm *i* in year *t*.
Age	Natural logarithm of establishment year of firm *i* in year *t*.
Lev	The ratio of total debt to total assets of firm *i* in year *t*.
Growth	The growth rate of total sales of firm *i* in year *t*.
Labor	Natural logarithm of total employees of firm *i* in year *t*.
State	1 if firm *i* is a state-owned enterprise and 0 otherwise.
Board	The ratio of independent director scale to total director scale.

3.3. Model Specification

The difference-in-differences (DID) model can weaken endogenous effects and be used to reasonably measure policy effectiveness. The DID method can control for both the unobservable individual heterogeneity among the samples and the unobservable overall factors that change over time, thereby yielding an unbiased estimate of the policy effect. The AAQS (2012) provides a quasi-natural experiment: on the one hand, it creates differences before and after the implementation of the standards in the same area; on the other hand, it creates differences between areas implementing the standards and those not implementing them at the same point in time. Additionally, the standards are considered a policy experiment, and the DID method is suitable for analyzing the effects of such policies.

Therefore, this paper realizes the empirical research of DID estimation by constructing a quasi-natural experiment of the policy of the AAQS (2012). In DID, the first difference demonstrates the policy impact on FTP difference in whether the enterprise belongs to a city impacted by the policy; the second difference indicates the time difference, analyzing the differences in FTP of selected firms before or after the operation of the new policy. Hence, this model can indicate the TFP differences of polluting firms in pilot cities and those that are not, both pre- and post-implementation of the policy.

Our developed model is outlined below:

$$TFP_{it} = \beta_0 + \beta_1 Treat \times Post + \sum Controls + \sum Year + \sum Region + \varepsilon_{it} \quad (8)$$

In the model, TFP_{it} represents the TFP of selected firms. The dummy variable *Treat* is assigned a value of 1 for firm *I* if it is located in one of the 74 pilot cities and 0 if it is in one of the 192 non-pilot cities. Similarly, the dummy variable *Post* is set to 1 for any

year t that is 2012 onwards and 0 for years before 2012; the coefficient β_1 of *Treat* × *Post* is utilized to gauge the influence of the AAQS (2012) policy. *Controls* encompasses all control variables detailed in Section 3.2.3. *Year* and *Region* describe the year and region fixed effect, respectively; ε_{it} signifies the error term.

4. Results

4.1. Descriptive Statistics

Table 4 shows the descriptive statistic results of the variables. The mean value of *TFP* is 2.327, and the standard deviation, minimum, median, and maximum values are 0.817, −2.551, 2.266, and 6.905, respectively. The average value of *Treat* is 0.544, which shows that 54.4% of polluting firms are in the pilot cities and would be affected by the new standard. Next, descriptive statistics of the control parameters are provided. The mean values of firm characteristic variables including *Size*, *Age*, *Lev*, *Growth*, *Labor*, *Board*, and *Analyst* are 8.539, 2.887, 45.906, 11.605, 7.967, 0.370, and 1.721, respectively. The mean value of *State* is 0.483, which indicates that 48.3% of the polluting firms in the sample are state-owned firms.

Table 4. Descriptive statistics.

Variables	Obs.	Mean	S.D.	Min	Median	Max
TFP	7917	2.327	0.817	−2.551	2.266	6.905
Treat	7917	0.544	0.498	0.000	1.000	1.000
Post	7917	0.727	0.445	0.000	1.000	1.000
Size	7917	8.539	1.339	5.771	8.357	12.464
Age	7917	2.887	0.314	2.079	2.890	3.611
Lev	7917	45.906	20.850	5.512	46.137	98.424
Growth	7917	11.605	27.197	−49.231	8.712	132.169
Labor	7917	7.967	1.209	4.927	7.932	11.023
State	7917	0.483	0.500	0.000	0.000	1.000
Board	7917	0.370	0.051	0.300	0.333	0.571
Analyst	7917	1.721	1.424	0.000	1.609	4.511

4.2. Baseline Regression Results

In the baseline regression, we sequentially add the year and region fixed effect and control variables. The regression results of the impact on the TFP of polluting firms by new standards are reported in Table 5. Column (1) is the regression results that join the interaction term *Treat* × *Post*; the correlation coefficient of *Treat* × *Post* is 0.070 and significant at the 1% level, indicating that the AAQS (2012) has a positive impact on the TFP of selected firms. Column (2) represents the results of *Treat* × *Post* with year and region fixed effects; the correlation coefficient of *Treat* × *Post* is 0.026 and still significant at the 1% level. With the control variables in columns (3) and (4), the correlation coefficients of *Treat* × *Post* are 0.033 and 0.026, respectively, and are both significant at the 1% level. The empirical study shows that as the implementation of the AAQS (2012) has been implemented effectively, the TFP of selected firms has increased significantly, which supports H1.

The probable reasons for the policy's favorable effect on TFP can be outlined as follows: On the one hand, the local government are expected to intensify their oversight of companies' manufacturing processes post-policy implementation. This heightened scrutiny is driven by the dual influence of central government directives and societal expectations [52]. Such increased monitoring is likely to lead to a reduction in environmental contamination, which, in turn, fosters an environment conducive to TFP enhancement. On the other hand, the policy-induced pressure compels businesses to invigorate their capacity for eco-friendly innovation. This proactive approach is adopted to circumvent financial penalties, thereby further propelling TFP growth [53].

Table 5. Baseline regression results.

Explanatory Variable	**Dependent Variable: *TFP***			
	(1)	**(2)**	**(3)**	**(4)**
Treat × *Post*	0.070 ***	0.026 ***	0.033 ***	0.026 ***
	(0.006)	(0.006)	(0.005)	(0.005)
Size			0.050 ***	0.034 ***
			(0.004)	(0.004)
Age			0.058 ***	0.024 **
			(0.008)	(0.010)
Lev			−0.004 ***	−0.004 ***
			(0.000)	(0.000)
Growth			0.001 ***	0.001 ***
			(0.000)	(0.000)
Labor			−0.081 ***	−0.078 ***
			(0.005)	(0.005)
State			0.017 ***	0.018 ***
			(0.004)	(0.005)
Board			−0.131 ***	−0.189 ***
			(0.039)	(0.038)
Analyst			0.027 ***	0.034 ***
			(0.002)	(0.002)
Constant	−0.029 ***	−0.031 **	0.230 ***	0.412 ***
	(0.003)	(0.014)	(0.034)	(0.039)
Year fixed effect	No	Yes	No	Yes
Region fixed effect	No	Yes	No	Yes
Obs.	7917	7917	7917	7917
Adj R^2	0.023	0.104	0.328	0.375

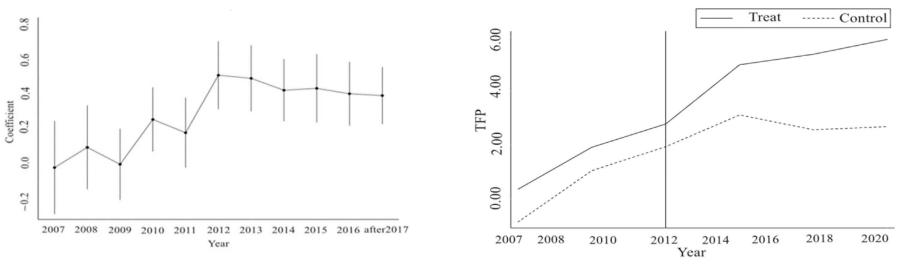
Note: t-statistics in parentheses (*** $p < 0.01$, ** $p < 0.05$).

4.3. Robust Test

In this section, we implement a variety of robustness checks to reinforce the findings from our primary analysis, including a parallel trend test, a placebo test, changing the proxy variables of TFP, controlling the impact of other policies, and comparing with PSM-DID regression results.

4.3.1. Parallel Trend Test

Although the DID method can better solve the endogenous problem in policy evaluation, the premise of its effectiveness is that it must meet the parallel trend hypothesis. This premise requires that the TFP of polluting firms in the control group and the experimental group must have the same change trend before being impacted by the policy. Therefore, this paper uses two methods to test it. The analysis results are shown in Figure 2. The results of these two methods show that before the implementation of the AAQS (2012), the change trend of the control group and the experimental group is relatively consistent, and there is no significant difference. After 2012, the TFP of the experimental group is significantly higher than that of the control group, but the difference between the two shows a downward trend in subsequent years, indicating that the impact of the policy on TFP has a dynamic effect.



(**a**) Confidence interval graph. (**b**) Time trend graph.

Figure 2. Parallel trend test.

4.3.2. Placebo Test

The premise of the DID method is that there is no significant difference in the TFP of firms before the policy event. Hence, if the policy event is set in a period other than 2012, the estimation coefficient of the independent variable will not be significant. If the result is contrary to the expectation, it means that there are some potential unobservable factors affecting the TFP of firms, not just because of the impact of the launch of the new standard. In order to verify this premise, a placebo test is performed. This paper sets policy events in 2013 and 2014. The placebo test results are reported in Table 6. The estimation coefficient of the independent variable is not significant, so the impact of other potential unobservable factors on the TFP of polluting firms can be excluded.

Table 6. Placebo test results.

Explanatory Variable	**Dependent Variable: *TFP***	
	(1)	**(2)**
Treat × *Post*	0.027	0.018
	(0.018)	(0.019)
Constant	−0.224 *	−0.225 *
	(0.121)	(0.121)
Controls	7116	7116
Year fixed effect	0.502	0.502
Region fixed effect	193.518	192.630
Obs.	0.575	0.575
Adj R^2	2338.379	2338.793

Note: t-statistics in parentheses (* $p < 0.1$).

4.3.3. Change Proxy Variables of TFP

As mentioned before, there will inevitably be challenges related to measurement and technical accuracy, specifically simultaneity deviation and sample selectivity deviation in the estimation of TFP. One of the most prominent is the problem of simultaneity deviation. The above problems are overcome by a variety of methods, which leads to a variety of estimation methods of TFP. Therefore, this paper tests the robustness of TFP estimated by the ordinary least squares method (OLS), the LP method (Two-Step Estimation Method) [54], and Wooldridge estimation (one-step consistent estimation within the GMM framework) [55]. Table 7 presents the results of the robustness test; the correlation coefficients of *Treat* × *Post* are all significantly positive, which further shows that the AAQS (2012) improves the TFP of polluting firms.

Table 7. Results of changing the dependent variables for regression.

Explanatory Variable	***TFP*-OLS**	***TFP*-LP**	***TFP*-WRDG**
	(1)	**(2)**	**(3)**
Treat × *Post*	0.061 ***	0.121 ***	0.023 ***
	(0.019)	(0.017)	(0.005)
Constant	−0.498 ***	−0.440 ***	0.352 ***
	(0.129)	(0.117)	(0.041)
Controls	Yes	Yes	Yes
Year fixed effect	Yes	Yes	Yes
Region fixed effect	Yes	Yes	Yes
Obs.	7116	7116	7116
Adj R^2	0.254	0.464	0.365

Note: t-statistics in parentheses (*** $p < 0.01$).

4.3.4. Control the Impact of Other Policies

Considering that the TFP of polluting firms may be affected by other environmental policy factors, we exclude other policy factors from the following two aspects [56]. Firstly, the new Environmental Protection Law introduced in 2015 stipulates that firms need to implement relevant measures to reduce emissions and control pollution, which may have an impact on their total factor productivity. The potential impact of this policy is excluded by adding dummy variables for years after 2015. Secondly, since 2016, Zhejiang, Jiangxi, Guangdong, Guizhou, Gansu, and Xinjiang have all established green finance reform and innovation pilot zones. The business activities of firms, especially polluting firms, in the pilot areas may change, which is significantly different from other regions. Hence, we chose to exclude the sample data of these six provinces and autonomous regions to control the impact of this policy. The results presented in Table 8 indicate that after controlling the impact of other policies, the correlation coefficients of *Treat* × *Post* are all significant at the 1% level. The results prove that the AAQS (2012) does really improve the TFP of polluting firms.

Table 8. Results of controlling the impact of other policies' regression.

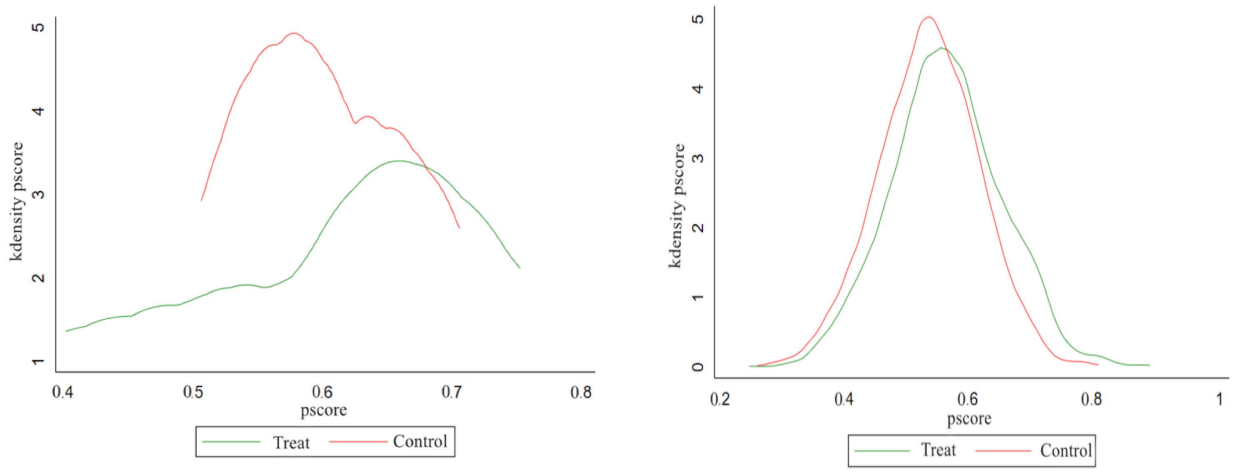
Explanatory Variable	**Dependent Variable: *TFP***	
	(1)	**(2)**
Treat × *Post*	0.027 ***	0.025 ***
	(0.005)	(0.006)
Constant	0.435 ***	0.487 ***
	(0.040)	(0.049)
Controls	Yes	Yes
Year fixed effect	Yes	Yes
Region fixed effect	Yes	Yes
Obs.	7917	5780
Adj R^2	0.390	0.405

Note: t-statistics in parentheses (*** $p < 0.01$).

4.3.5. PSM-DID Regression Results

Although the DID model can alleviate the endogenous problem through differences, it cannot solve the problem of sample selection error. In order to solve this problem, this study uses the propensity matching score method (PSM) to match the samples first and then makes an estimation. The PSM-DID method matches the treatment group with the control group, which can reduce potential bias caused by individual feature imbalance. In addition, it can perform more detailed matching based on individual features and attributes, improving the accuracy and reliability of matching. This can control the influence of potential confounding variables, making the treatment group and control group more similar before and after observation.

In the PSM, the firm characteristics are taken as the matching standard, and the balance test results are reported in Figures 3 and 4. It can be observed from the figures that compared with the results before matching, the standardization deviation of most variables is significantly reduced, which indicates that the PSM more effectively solves the problem of sample selection error. Based on two groups of matched samples, DID estimation has been conducted. The conclusive regression results are detailed in Table 9. The regression outcomes are similar to the basic regression results, which further shows that the AAQS (2012) significantly improves the TFP of polluting firms.



(**a**) Before matching. (**b**) After matching.

Figure 3. Probability density of score before and after matching.

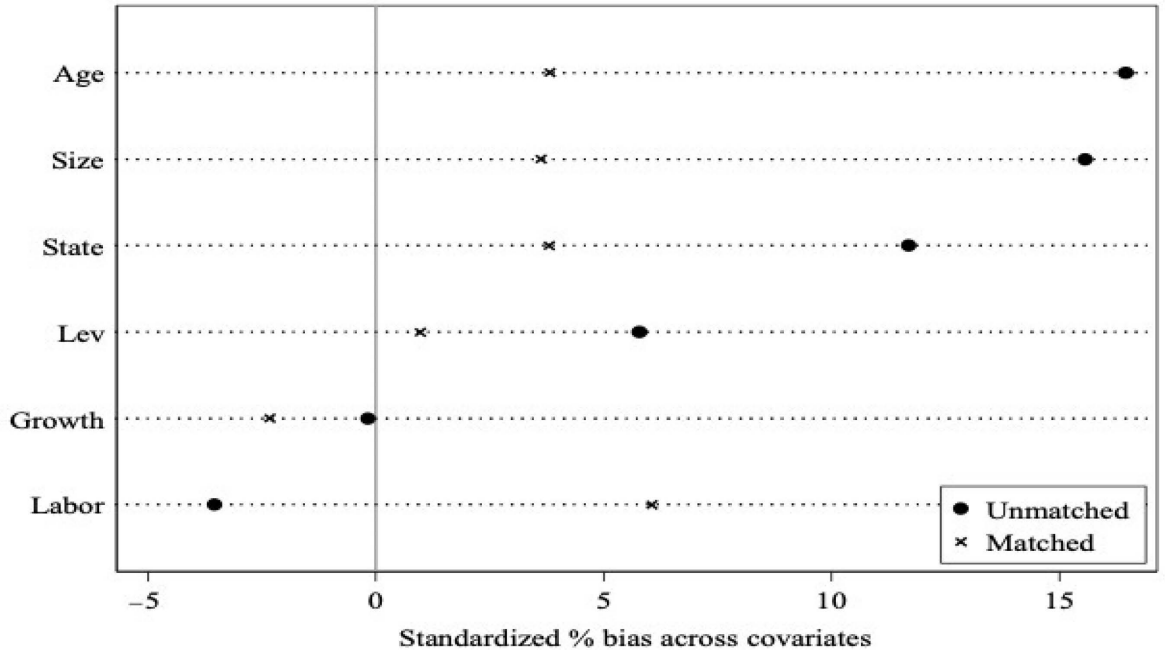


Figure 4. Standardized deviation of variables.

Table 9. PSM-DID regression results.

Explanatory Variable	Dependent Variable: *TFP*
Treat × *Post*	0.023 ***
	(0.006)
Constant	0.374 ***
	(0.050)
Controls	Yes
Year fixed effect	Yes
Region fixed effect	Yes
Obs.	6980
Adj R^2	0.374

Note: t-statistics in parentheses (*** $p < 0.01$).

5. Further Research

5.1. Possible Channels

In this section, we explore possible channels that can be used to explain the effect of environmental policy on TFP. Existing studies have delved into the influence of environmental regulations on the macro and sectoral levels, focusing on the "cost-effectiveness" and the "Porter hypothesis" within the framework of neoclassical economics [57]. These studies have concluded that both macroeconomic and microeconomic entities can attain a mutually beneficial outcome concerning economic performance and environmental conservation by embracing industrial transformation and technological innovation, all while operating within the confines of regulatory guidelines [58].

To carry out the objectives of air quality control, the pilot cities eliminated backward firms with excess capacity, high energy consumption, and low efficiency through supply-side structural reform, to foster the advancement and modernization of the urban industrial framework, leading to a reduction in industry concentration, and enabling firms with higher efficiency to obtain more production factors. The forced elimination or reorganization of some firms with enlarged pollution emissions in the pilot cities also optimizes the market structure and helps to further release economies of scale. The level of industrial concentration directly reflects the intensity of market competition. Market competition can promote the improvement of a firm's productivity based on the Darwinian selection mechanism. In a fierce market competition environment, companies need to continuously enhance their competitiveness and improve production efficiency to survive [59]. Syverson [60] conducted research on manufacturing industries with low concentration and sufficient competition, and the results showed that the average production level of companies was higher, but productivity was more dispersed. However, for non-manufacturing industries, Foster et al. [61] found that competition improves overall industry productivity by forcing inefficient companies to exit the market and allowing efficient companies to consolidate the market. Of course, besides improving productivity through self-selection mechanisms, competition can also encourage companies to improve efficiency by enhancing management levels [62].

This paper measures the industry concentration by using the Herfindahl–Hirschman Index (HHI) [63]. The regression results are shown in column (1) of Table 10. The correlation coefficient of *Treat* × *Post* is significantly negative, indicating that the implementation of the policy reduced the industry concentration. This indicates that under the pressure of air quality monitoring, firms will continuously achieve transformation and upgrading, promoting the optimization of internal resource allocation.

Table 10. Channel exploration.

Explanatory Variable	Dependent Variable: *HHI*	Dependent Variable: *Patent*
	(1)	(2)
Treat × *Post*	−0.008 **	0.055 ***
	(0.003)	(0.021)
Constant	1.044 ***	0.525 ***
	(0.025)	(0.158)
Controls	Yes	Yes
Year fixed effect	Yes	Yes
Region fixed effect	Yes	Yes
Obs.	7917	7917
Adj R^2	0.071	0.009

Note: t-statistics in parentheses (*** $p < 0.01$, ** $p < 0.05$).

Polluting firms in pilot cities pay more attention to the innovation of high-tech or advanced environmental protection equipment and production processes, to achieve the dual goals of economic growth and air pollution control, which will improve their TFP. Existing research indicates a positive relationship between innovation and total factor productivity. Research and development (R&D) investment has made significant contributions to the

growth of total factor productivity in China [64]. This conclusion has also been confirmed in other regions [65].

In this paper, the number of patent authorizations is used as the proxy variable of firms' innovation level, and to eliminate the impact of firm scale, the firms' operating revenues are used for standardization. The results are shown in column (2) of Table 10. The coefficient of *Treat* × *Post* is significantly positive, indicating that the implementation of the policy has improved the innovation level of polluting firms in pilot cities. This indicates that under the pressure of air quality monitoring, firms will transform their development methods and promote the optimization of internal resource allocation through investment in organizational, technological, or market innovation.

5.2. Heterogeneity Analysis

Urbanization can stimulate the vitality and potential of the market economy, stimulate new market demand, and guide the upgrading of industrial structures [66]. The process of urbanization and industrial structure upgrading has the characteristics of coordination and synchronization [67]. Polluting firms situated in cities with a high degree of urbanization usually play an important role in the reform of industrial structure and innovation activities. They are usually more sensitive to environmental policies, especially newly issued air pollution quality standards, and meet their environmental stewardship obligations.

In order to investigate the heterogeneity of polluting firms with different urbanization levels, according to the median urbanization degree measured by the luminous index, the research sample is divided into two groups: high urbanization and low urbanization. The regression results are reported in columns (1) and (2) in Table 11. The results show that the correlation coefficient of *Treat* × *Post* in the high-urbanization group is significantly positive, while it cannot be found in the low-urbanization group. The result of the Chow Test proves the significance of the coefficient difference. It indicates that compared with polluting firms in low-urbanization cities, the new standard plays a more important role in promoting the TFP of polluting firms in high-urbanization cities. These results support H2.

Table 11. Heterogeneity analysis.

Explanatory Variable	**Dependent Variable: *TFP***			
	High Urbanization	**Low Urbanization**	**Over-Investment**	**Non-Over-Investment**
	(1)	**(2)**	**(3)**	**(4)**
Treat × *Post*	0.027 ***	0.015	0.054 **	0.002
	(0.006)	(0.010)	(0.025)	(0.024)
Constant	0.435 ***	0.535 ***	−0.637 ***	0.184
	(0.037)	(0.066)	(0.179)	(0.160)
Chow Test	0.022 ***		0.087 ***	
Controls	Yes	Yes	Yes	Yes
Year fixed effect	Yes	Yes	Yes	Yes
Region fixed effect	Yes	Yes	Yes	Yes
Obs.	4567	3350	2962	4154
Adj R^2	0.373	0.388	0.552	0.489

Note: t-statistics in parentheses (*** $p < 0.01$, ** $p < 0.05$).

This research indicates that firms within the polluting sector in high-urbanization cities are more inclined to engage in innovative endeavors in response to the introduction of stringent new environmental standards. In contrast, businesses in less urbanized areas may opt for alternative strategies, such as reducing production levels, to mitigate their emissions, rather than actively pursuing innovation initiatives.

Investment efficiency reflects the relationship between the effective results achieved by a company's investment activities and the investment, and reflects the efficiency of the

company's use of funds [68]. As an important criterion for evaluating corporate investment behavior, investment efficiency will have a significant impact on the allocation strategy of corporate funds, including investment decisions and dividend policies [69]. Polluting firms with over-investment experience receive more investigation and are usually more bound by the new air quality monitoring policy; thus, the new policy has a more obvious impact on these firms' TFP.

To investigate the heterogeneity of polluting firms with different over-investment experiences, based on the method of Biddle et al., this paper divides the research sample into two groups: over-investment or not [70]. The regression results are reported in columns (3) and (4) in Table 11. The results show that the correlation coefficient of *Treat* × *Post* in the over-investment group is significantly positive at the 5% level, but is not significant in the other group. And the Chow Test also proves the coefficient difference. It indicates that compared with firms without over-investment experience, the impact of the new standard is more significant on firms with over-investment experience, which supports H3.

This result indicates that the new standard of air quality monitoring has brought certain cost pressure to firms, and over-investment firms are more likely to include the expenses incurred by implementing clean production in their operating costs. Over-investment firms, with the goal of long-term survival and profitability, will reconfigure production factor resources, reduce investment in polluting and inefficient production departments, and instead increase investment in clean and efficient production departments, thereby improving the total factor productivity of the enterprise.

6. Discussions

The empirical results of this study indicate that Ambient Air Quality Standard policies have a promoting effect on the TFP of firms. Therefore, it is necessary to fully leverage the guiding and driving role of ecological environment protection to continuously promote enterprise development and achieve comprehensive green transformation of the economy and society. These results suggest that the government should strengthen air pollution control efforts and improve the central ecological environment protection supervision and control system. Actively responding to air pollution control policies is an obligation that firms should fulfill.

Exploring the channels shows that the new standard mainly affects TFP by adjusting industry concentration and firm innovation capabilities. Through policy support and the relaxation of market access restrictions, governments should encourage small and medium-sized enterprises (SMEs) to enter the market, increase market competition vitality, and prevent excessive monopoly of the market by a single large enterprise. Furthermore, research has found that technological innovation capability not only serves as an intermediary variable affecting the TFP through air quality monitoring, but also promotes the improvement of TFP itself. All regions should increase technological investment, guide industries towards high-value-added and high-tech directions, better adjust the industrial structure, and reduce dependence on high-emission, high-energy-consuming industries.

In the analysis of heterogeneity, the perspective of consideration is more comprehensive. Heterogeneity analysis shows that areas with high urbanization are more sensitive to air pollution control standards, and the TFP of polluting firms with over-investment experience are affected more by the new standard. This means the government should develop and implement targeted policies for different regions and firms. When formulating policies, it is necessary to consider the differences between firms in different levels of urbanization and between over-investment and non-over-investment firms. The government can introduce targeted measures and regulations to achieve maximum implementation effectiveness, for example, further strengthening the monitoring and control of firms in low-urbanization areas, strengthening compliance pressure on non-over-investment firms, and urging them to fulfill their environmental protection obligations.

This paper indicates that the implementation of environmental policy does not necessarily hinder economic development. On the contrary, appropriate air quality monitoring

can promote the co-development of the environment and economy. The research results help us to have a clearer understanding of the role and effectiveness of Ambient Air Quality Standard policies. Furthermore, the results have important theoretical guidance and practical significance for coordinating the relationship between environmental policies and sustainable economic growth.

7. Conclusions and Limitations

Taking the Ambient Air Quality Standard (2012) as a typical represent of air quality monitoring, this paper uses a quasi-natural experiment by the DID method to examine the influence of air quality monitoring on the TFP of polluting firms in China. Our study finds that air quality monitoring can increase polluting firms' TFP. A series of robust tests including a parallel trend test, placebo test, and PSM-DID are also presented to demonstrate the reliable validity of the results. The empirical results indicate that air quality monitoring, represented by the Ambient Air Quality Standard (2012), has a promoting effect on TFP. Exploring the channels, it shows that the new standard mainly affects TFP by adjusting industry concentration and firm innovation capabilities. Heterogeneity analysis shows that firms in high-urbanization areas are more sensitive to air quality monitoring standards, as are those with over-investment experience.

This study has yielded significant insights and guidance for governmental policy-making and scholarly inquiry into the nexus of air quality monitoring and economic expansion. However, certain restrictions are worth acknowledging. Primarily, our research was confined to enterprises within the realm of polluting industries, neglecting to examine the repercussions of air quality monitoring on businesses in non-polluting sectors, as well as the influence of the greening of polluting industries on their non-polluting counterparts. Additionally, the scope of our investigation was constrained by the duration of the observation period, which spanned from 2007 to 2020. Future studies could enhance and broaden our comprehension of the temporal dynamics of policy impacts by refining the research methodologies and frameworks employed.

Author Contributions: Conceptualization, X.L. and L.H.; writing—original draft preparation, X.L., L.H. and J.H.; writing—review and editing, X.L., L.H. and R.Z. All authors have read and agreed to the published version of the manuscript.

Funding: This work is supported by the Research Initiation Fund Project of the North China University of Technology (110051360002), the Yuxiu Innovation Project of NCUT (2024NCUTYXCX114, 2024NCUTYXCX212), and the University of International Business and Economics School Program (23PYTS35).

Institutional Review Board Statement: Not applicable.

Informed Consent Statement: Not applicable.

Data Availability Statement: Data will be made available on request.

Conflicts of Interest: The authors declare no conflicts of interest.

References

1. Chen, P.; Dagestani, A.A. What Lies about Circular Economy Practices and Performance? Fresh Insights from China. *J. Clean. Prod.* **2023**, *416*, 137893. [CrossRef]
2. Zhang, S.; Cheng, L.; Ren, Y.; Yao, Y. Effects of Carbon Emission Trading System on Corporate Green Total Factor Productivity: Does Environmental Regulation Play a Role of Green Blessing? *Environ. Res.* **2024**, *248*, 118295. [CrossRef] [PubMed]
3. Tanaka, S. Environmental Regulations on Air Pollution in China and Their Impact on Infant Mortality. *J. Health Econ.* **2015**, *42*, 90–103. [CrossRef] [PubMed]
4. Chang, T.Y.; Zivin, J.G.; Gross, T.; Neidell, M. The Effect of Pollution on Worker Productivity: Evidence from Call Center Workers in China. *Am. Econ. J. Appl. Econ.* **2019**, *11*, 151–172. [CrossRef]
5. He, J.; Liu, H.; Salvo, A. Severe Air Pollution and Labor Productivity: Evidence from Industrial Towns in China. *Am. Econ. J. Appl. Econ.* **2019**, *11*, 173–201. [CrossRef]
6. Vyas, V.; Mehta, K.; Sharma, R. The Nexus Between Toxic-Air Pollution, Health Expenditure, and Economic Growth: An Empirical Study Using ARDL. *Int. Rev. Econ. Financ.* **2023**, *84*, 154–166. [CrossRef]

7. Nazarenko, Y.; Pal, D.; Ariya, P.A. Air Quality Standards for the Concentration of Particulate Matter 2.5, Global Descriptive Analysis. *Bull. World Health Organ.* **2021**, *99*, 125–137. [CrossRef]
8. Guo, X.; Xu, J.J. New Ambient Air Quality Standards, Human Capital Flow, and Economic Growth: Evidence from an Environmental Information Disclosure Policy in China. *J. Clean. Prod.* **2024**, *434*, 140168. [CrossRef]
9. Regional Office for Europe, World Health Organization. *Guidance for Setting Air Quality Standards*; WHO: Geneva, Switzerland, 1997.
10. Liu, X.Y.; Wen, H.X.; Ding, D.D. The Impact of New Ambient Air Quality Standards on Green Total Factor Energy Efficiency: Evidence from an Environmental Information Disclosure Policy in China. *Front. Env. Ment. Sci.* **2023**, *11*, 1120893. [CrossRef]
11. *GB 3095-2012*; Ambient Air Quality Standards. Ministry of Ecology and Environment of the People's Republic of China, Chinese Academy of Environmental Sciences, China Environmental Monitoring Station: Beijing, China, 2012. (In Chinese)
12. Solow, R.M. Technical Change and the Aggregate Production Function. *Rev. Econ. Stat.* **1957**, *39*, 312–320. [CrossRef]
13. Goldar, B.; Das, P.C.; Dutta, S. The Role of Services in India's Post-Reform Economic Growth. *Struct. Change Econ. D* **2024**, *68*, 355–370. [CrossRef]
14. Jia, F.; Ma, X.; Xu, X.; Xie, L. The Differential Role of Manufacturing and Non-Manufacturing TFP Growth in Economic Growth. *Struct. Chang. Econ. D* **2020**, *52*, 174–183. [CrossRef]
15. Liu, C.; Yang, Y.; Xu, Y. Do Governance Patterns of Environmental Regulation Affect Firm's Technological Innovation: Evidence from China. *J. Clean. Prod.* **2023**, *425*, 138767.
16. Ma, C.; Xie, R. Structural, Innovation and Efficiency Effects of Environmental Regulation: Evidence from China's Carbon Emissions Trading Pilot. *Environ. Resour. Econ.* **2020**, *75*, 741–768.
17. Iraldo, F.; Testa, F.; Frey, M. Is an Environmental Management System Able to Influence Environmental and Competitive Performance? The Case of the Eco-management and Audit Acheme (EMAS) in the European Union. *J. Clean. Prod.* **2009**, *17*, 1444–1452. [CrossRef]
18. Ambec, S.; Cohen, M.A.; Elgie, S.; Lanoie, P. The Porter Hypothesis at 20: Can Environmental Regulation Enhance Innovation and Competitiveness. *Rev. Env. Econ. Policy* **2013**, *7*, 2–22. [CrossRef]
19. Lanoie, P.; Patry, M.; Lajeunesse, R. Environmental Regulation and Productivity: Testing the Porter Hypothesis. *J. Prod. Anal.* **2008**, *30*, 121–128. [CrossRef]
20. Löschel, A.; Lutz, B.J.; Managi, S. The Impacts of the EU ETS on Efficiency and Economic Performance—An Empirical Analyses for German Manufacturing Firms. *Resour. Energy Econ.* **2019**, *56*, 71–95. [CrossRef]
21. Xiao, J.; Li, G.; Zhu, B.; Xie, L.; Hu, Y.; Huang, J. Evaluating the Impact of Carbon Emissions Trading Scheme on Chinese firms' Total Factor Productivity. *J. Clean. Prod.* **2021**, *306*, 127104. [CrossRef]
22. Pan, D.; Yu, Y.; Kong, F. Quantifying the Effectiveness of Environmental Regulations on Green Total Factor Productivity: Evidence Based on China's Environmental Protection Interview Program. *Int. J. Environ. Res. Public Health* **2023**, *20*, 2980. [CrossRef]
23. Porter, M.E. America's Green Strategy. In *Reader in Business and the Environment*; Welford, R., Starkey, R., Eds.; Taylor & Francis: Abingdon, UK, 1991; p. 33.
24. Hamamoto, M. Environmental Regulation and the Productivity of Japanese Manufacturing Industries. *Resour. Energy Econ.* **2006**, *28*, 299–312. [CrossRef]
25. Testa, F.; Iraldo, F.; Frey, M. The Effect of Environmental Regulation on Firms' Competitive Performance: The Case of the Building & Construction Sector in Some EU Regions. *J. Environ. Manag.* **2011**, *92*, 2136–2144.
26. Granderson, G.; Prior, D. Environmental Externalities and Regulation Constrained Cost Productivity Growth in the US Electric Utility Industry. *J. Prod. Anal.* **2013**, *39*, 243–257. [CrossRef]
27. Rubashkina, Y.; Galeotti, M.; Verdolini, E. Environmental Regulation and Competitiveness: Empirical Evidence on the Porter Hypothesis from European Manufacturing Sectors. *Energ. Policy* **2015**, *83*, 288–300. [CrossRef]
28. Liu, P.; Huang, W.; Chen, H. Can the National Green Industrial Policy Improve Production Efficiency of Enterprises?—Evidence from China. *Sustainability* **2020**, *12*, 6839. [CrossRef]
29. Li, Y.; Ding, L.; Yang, Y. Can the Introduction of an Environmental Target Assessment Policy Improve the TFP of Textile Enterprises? A Quasi-Natural Experiment Based on the Huai River Basin in China. *Sustainability* **2020**, *12*, 1696. [CrossRef]
30. Xie, Y.; Wu, D.; Li, X.; Tian, S. How Does Environmental Regulation Affect Productivity? The Role of Corporate Compliance Strategies. *Econ. Model.* **2023**, *126*, 106408. [CrossRef]
31. Liu, M.; Tan, R.; Zhang, B. The Costs of "Blue Sky": Environmental Regulation, Technology Upgrading, and Labor Demand in China. *J. Dev. Econ.* **2021**, *150*, 10261. [CrossRef]
32. Broberg, T.; Marklund, P.; Samakovlis, E.; Hammar, H. Testing the Porter Hypothesis: The Effects of Environmental Investments on Efficiency in Swedish Industry. *J. Prod. Anal.* **2013**, *40*, 43–56. [CrossRef]
33. Wang, Y.; Sun, X.; Guo, X. Environmental Regulation and Green Productivity Growth: Empirical Evidence on the Porter Hypothesis from OECD Industrial Sectors. *Energy Pol.* **2019**, *132*, 611–619. [CrossRef]
34. Habermann, F.; Fischer, F.B. Corporate Social Performance and the Likelihood of Bankruptcy: Evidence from a Period of Economic Upswing. *J. Bus. Ethics* **2023**, *182*, 243–259. [CrossRef]
35. Wang, C.; Wu, J.; Zhang, B. Environmental Regulation, Emissions and Productivity: Evidence from Chinese COD-Emitting Manufacturers. *J. Environ. Econ. Manag.* **2018**, *92*, 54–73. [CrossRef]

36. Li, C. How Does Environmental Regulation Affect Different Approaches of Technical Progress?—Evidence from China's Industrial Sectors from 2005 to 2015. *J. Clean. Prod.* **2019**, *209*, 572–580. [CrossRef]
37. Jiang, Y.; Guo, Y.; Muhammad, F.B.; Shahbaz, M. Do Renewable Energy, Environmental Regulations, And Green Innovation Matter for China's Zero Carbon Transition: Evidence from Green Total Factor Productivity. *J. Environ. Manag.* **2024**, *352*, 120030. [CrossRef] [PubMed]
38. Peng, J.; Xiao, J.; Zhang, L.; Wang, T. The Impact of China's 'Atmosphere Ten Articles' Policy on Total Factor Productivity of Energy Exploitation: Empirical Evidence Using Synthetic Control Methods. *Resour. Policy* **2020**, *65*, 101544. [CrossRef]
39. Owens, E.O.; Patel, M.M.; Kirrane, E.; Long, T.C.; Brown, J.; Cote, I.; Ross, M.A.; Dutton, S.J. Framework for Assessing Causality of Air Pollution-Related Health Effects for Reviews of the National Ambient Air Quality Standards. *Regul. Toxicol. Pharm.* **2017**, *88*, 332–337. [CrossRef] [PubMed]
40. Wang, K.; Yin, H.; Chen, Y. The Effect of Environmental Regulation on Air Quality: A Study of New Ambient Air Quality Standards in China. *J. Clean. Prod.* **2019**, *215*, 268–279. [CrossRef]
41. Ma, G.; Wang, J.; Yu, F.; Zhang, Y.; Cao, D. An Assessment of the Potential Health Benefits of Realizing the Goals for PM10 in the Updated Chinese Ambient Air Quality Standard. *Front. Env. Sci. Eng.* **2016**, *10*, 288–298. [CrossRef]
42. Liu, S.; Yang, D.; Liu, N.; Liu, X. The Effects of Air Pollution on Firms' Internal Control Quality: Evidence from China. *Sustainability* **2019**, *11*, 5068. [CrossRef]
43. 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]
44. Chen, P.; Zhao, R.; Chu, Z. The Relationship Between Dynamic Monitoring Network Plans and Eco-Efficiency–New Evidence from Atmospheric Quality Monitoring Policy in China. *J. Environ. Manag.* **2023**, *348*, 119297. [CrossRef] [PubMed]
45. Arrow, K.; Bolin, B.; Costanza, R.; Dasgupta, P.; Folke, C.; Holling, C.S.; Jansson, B.O.; Levin, S.; Mäler, K.G.; Perrings, C.; et al. Economic Growth, Carrying Capacity, and the Environment. *Ecol. Econ.* **1995**, *15*, 91–95. [CrossRef]
46. Luo, K.; Li, G.; Fang, C.; Sun, S. PM2.5 Mitigation in China: Socioeconomic Determinants of Concentrations and Differential Control Policies. *J. Environ. Manag.* **2018**, *213*, 47–55. [CrossRef] [PubMed]
47. Sam, A.G.; Zhang, X. Value Relevance of the New Environmental Enforcement Regime in China. *J. Corp. Financ.* **2020**, *62*, 101573. [CrossRef]
48. Chen, S.; Sun, Z.; Tang, S.; Wu, D. Government Intervention and Investment Efficiency: Evidence from China. *J. Corp. Financ.* **2011**, *17*, 259–271. [CrossRef]
49. Deng, L.; Jiang, P.; Li, S.; Liao, M. Government Intervention and Firm Investment. *J. Corp. Financ.* **2020**, *63*, 101231. [CrossRef]
50. Olley, G.S.; Pake, A. The Dynamics of Productivity in the Telecommunications Equipment Industry. *Econometrica* **1996**, *64*, 1263–1297. [CrossRef]
51. Francoeur, C.; Melis, A.; Gaia, S.; Aresu, S. Green or Greed? An Alternative Look at CEO Compensation and Corporate Environmental Commitment. *J. Bus. Ethics* **2017**, *140*, 439–453. [CrossRef]
52. Liao, X.; Shi, X.R. Public Appeal, Environmental Regulation, And Green Investment: Evidence from China. *Energ. Policy* **2018**, *119*, 554–562. [CrossRef]
53. Feng, Z.; Chen, W. Environmental Regulation, Green Innovation, And Industrial Green Development: An Empirical Analysis Based on the Spatial Durbin Model. *Sustainability* **2018**, *10*, 223. [CrossRef]
54. Cheng, Z.; Zhu, Y. Does Stock Market Liberalization Increase Company TFP? Evidence from the Shanghai-Shenzhen-Hong Kong Stock Connect Program in China. *Econ. Syst.* **2024**, 101240. [CrossRef]
55. Wooldridge, J.M. On Estimating Firm-Level Production Functions Using Proxy Variables to Control for Un-observables. *Econ. Lett.* **2009**, *104*, 112–114. [CrossRef]
56. Si, L.; Cao, H. Does Green Credit Policies Improve Corporate Environmental Social Responsibility—The Perspective of External Constraints and Internal Concerns. *China Ind. Econ.* **2022**, *4*, 137–155.
57. Huang, J.; Zhao, J.; Cao, J. Environmental Regulation and Corporate R & D Investment-Evidence from a Quasi-Natural Experiment. *Int. Rev. Econ. Financ.* **2021**, *72*, 154–174.
58. Cai, X.; Zhu, B.; Zhang, H.; Li, L.; Xie, M. Can Direct Environmental Regulation Promote Green Technology Innovation in Heavily Polluting Industries? Evidence from Chinese Listed Companies. *Sci. Total Environ.* **2020**, *746*, 140810. [CrossRef] [PubMed]
59. Foster, L.; Haltiwanger, J.; Krizan, C.J. Aggregate Productivity Growth: Lessons from Microeconomic Evidence. In *New Developments in Productivity Analysis*; University of Chicago Press: Chicago, IL, USA, 1998.
60. Syverson, C. Product Substitutability and Productivity Dispersion. *Rev. Econ. Stat.* **2004**, *86*, 534–550. [CrossRef]
61. Foster, L.; Haltiwanger, J.; Krizan, C.J. Market Selection, Reallocation, And Restructuring in the Us Retail Trade Sector in the 1990S. *Rev. Econ. Stat.* **2006**, *88*, 748–758. [CrossRef]
62. Ju, S.; Xie, J.; Tang, H. The Impact of Competition on Operational Efficiency of Ports: Empirical Evidence from Chinese Coastal Port-Listed Companies. *Res. Transp. Bus. Manag.* **2023**, *46*, 100939. [CrossRef]
63. Brezina, I.; Pekár, J.; Čičková, Z.; Reiff, M. Herfindahl–Hirschman Index Level of Concentration Values Modification and Analysis of Their Change. *Cent. Eur. J. Oper. Res.* **2016**, *24*, 49–72. [CrossRef]
64. Huang, J.; Cai, X.; Huang, S.; Tian, S.; Lei, H. Technological Factors and Total Factor Productivity in China: Evidence Based on a Panel Threshold Model. *China Econ. Rev.* **2019**, *54*, 271–285. [CrossRef]

65. Sharif, N.; Chandra, K.; Mansoor, A.; Sinha, B.K. A Comparative Analysis of Research and Development Spending and Total Factor Productivity Growth in Hong Kong, Shenzhen, Singapore. *Struct. Chang. Econ. Dyn.* **2021**, *57*, 108–120. [CrossRef]
66. Li, C. Research on the Impact of New Urbanization on Industrial Transformation and Upgrading. *J. Econ. Trade Mark. Manag.* **2023**, *5*, 27–37. [CrossRef]
67. Wei, L.; Zhang, H.; Zhang, Y. The Impact of Technological Innovation and Industrial Structure Upgrading on New Urbanization: An Empirical Analysis Based on Panel Quantile Regression. *Mod. Econ.* **2021**, *12*, 1463–1485. [CrossRef]
68. Ahmed, B.; Akbar, M.; Sabahat, T.; Ali, S.; Hussain, A.; Akbar, A.; Xie, H.M. Does Firm Life Cycle Impact Corporate Investment Efficiency? *Sustainability* **2021**, *13*, 197. [CrossRef]
69. Samet, M.; Jarboui, A. How Does Corporate Social Responsibility Contribute to Investment Efficiency. *J. Multinatl. Financ. Manag.* **2017**, *40*, 33–46. [CrossRef]
70. Biddle, G.C.; Hilary, G.; Verdi, R.S. How Does Financial Reporting Quality Relate to Investment Efficiency? *J. Account. Econ.* **2009**, *48*, 112–131. [CrossRef]

Disclaimer/Publisher's Note: The statements, opinions and data contained in all publications are solely those of the individual author(s) and contributor(s) and not of MDPI and/or the editor(s). MDPI and/or the editor(s) disclaim responsibility for any injury to people or property resulting from any ideas, methods, instructions or products referred to in the content.