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Regional Differences in $PM_{2.5}$ Environmental Efficiency and Its Driving Mechanism in Zhejiang Province, China

Xuejuan Fang [1,2,3], Bing Gao [1,3,*], Shenghui Cui [1,3,*], Lei Ding [4], Lihong Wang [1,2,3] and Yang Shen [4]

1 Key Laboratory of Urban Environment and Health, Institute of Urban Environment, Chinese Academy of Sciences, Xiamen 361021, China
2 University of Chinese Academy of Sciences, No. 19(A) Yuquan Road, Beijing 100049, China
3 Xiamen Key Lab of Urban Metabolism, Xiamen 361021, China
4 Industrial Economic Research Center around Hangzhou Bay, Ningbo Polytechnic, Ningbo 315800, China
* Correspondence: binggao@iue.ac.cn (B.G.); shcui@iue.ac.cn (S.C.)

Abstract: Improving the digital economy and environmental governance efficiency are important methods for current high-quality economic development. Based on the panel data of 11 cities in Zhejiang, on the eastern coast of China, fine particulate matter smaller than a 2.5 µm ($PM_{2.5}$) environmental efficiency (PMEE) was measured by the undesirable output Slack-Based Measure-Data Envelopment Analysis (SBM-DEA) model. The fixed effect regression model, the divergences in the difference model and other empirical methods were obtained to test the driving mechanism of social-economic factors on the PMEE. The results showed that: (1) the concentration of $PM_{2.5}$ was continually decreasing, and environmental quality experienced a continuous improvement in Zhejiang province in the observation period, although cities such as Hangzhou, Jiaxing and Shaoxing have relatively severe $PM_{2.5}$ pollution. (2) The total average value of PMEE in Zhejiang was 0.6430 over the observation period, while there was still a lot of room for improvement when compared to the production frontier. Additionally, PMEE in each city showed a fluctuating growth trend. Cities with a higher PMEE were mainly Zhoushan, Hangzhou and Ningbo. (3) The level of the digital economy had a positive role in promoting the PMEE, which was statistically significant. The level of pollution control and technological innovation also had a significantly positive effect. However, the ratio of the industrial output value to the gross domestic product (GDP) presented a negative effect on the PMEE. In the future, it is suggested that the development of the urban digital economy should be accelerated in an all-around way to improve the efficiency of government pollution control and to improve the technical efficiency of $PM_{2.5}$ via innovative technological progress.

Keywords: $PM_{2.5}$; SBM-DEA; environmental efficiency; digital economy; Zhejiang province

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1. Introduction

Improving the efficiency of environmental governance is a crucial measure in order to fight a tough battle against environmental pollution and guarantee high-quality economic development [1–3]. At present, China is facing a severe challenge in air pollution control [4,5]. According to the data announced by the Ministry of Ecology and Environment, in 2020, about 33 percent of 337 cities in China did not meet the Class II national standard for the concentration of fine particulate matter smaller than 2.5 µm ($PM_{2.5}$), which is defined as a fine inhalable particle with a diameter less than 2.5 µm. The ozone concentration fluctuated and increased, and regional severe air pollution weather took place frequently. Thus, it is of great practical significance to continually strengthen the control of air pollution and to improve the efficiency of a reduction in $PM_{2.5}$ emissions [6,7].

Meanwhile, the research on the socio-economic driving factors of air pollution provides an essential reference for environmental pollution control [8]. Many scholars have discussed the causes of air pollution, smog, and pollution reduction paths from different perspectives, such as economic growth, foreign investment, industrial structure, environmental regulation, fiscal decentralization, population agglomeration, urbanization development, and technological innovation [9–11]. At present, China's economy has proceeded into the era of Industry 4.0, and the digital economy has become a crucial propulsion power for high-quality economic development, playing a vital role in transforming the economic development mode and promoting the construction of ecological civilization [12,13]. However, existing research on the relationship between the digital economy and environmental pollution is still in its infancy [14–18], especially since there is a lack of research on disclosing the relationship between the digital economy and atmospheric environmental efficiency [19]. Taking into account natural conditions, the economy, technology and the demographic scale of cities in different regions, it is necessary to examine scientifically and systematically the efficiency of air pollution in various cities, the potential efficiency of the effect of reducing emissions, and the factors affecting atmospheric environmental efficiency. The results can put forward countermeasures and suggestions for regional air pollution control and air quality improvement [20,21].

To account for these, this study selected a key area of air pollution prevention and a typical area of digital economic development, Zhejiang province, as a case study. The mass concentration values of $PM_{2.5}$ and the relevant socioeconomic data of 11 cities in Zhejiang province from 2006 to 2019 were obtained, and the $PM_{2.5}$ environmental efficiency (PMEE) was calculated with the undesirable output Slack-Based Measure-Data Envelopment Analysis (SBM-DEA) model. In this study, we defined PMEE as the environmental cost of $PM_{2.5}$ pollution paid by regional producers over a period of time using various factors to conduct economic activities. Subsequently, taking the digital economy as the core explanatory variable, the panel fixed effect model, difference-in-differences (DID), and other multi-dimensional systems were used to investigate the driving mechanism of PMEE's change. Finally, it proposed countermeasures and recommendations for improving the PMEE and controlling $PM_{2.5}$ pollution effectively.

The main contributions of this study were: (1) For coastal areas, the PMEE measurement model was established at the city level, which was helpful in strengthening the control and management of pollutants; (2) Taking the digital economy as the core explanatory variable, the mechanism of the influence of PMEE was revealed, which was conducive to the regulation of the digital economy with regard to environmental pollutants.

2. Literature Review

Environmental efficiency represents the environmental performance level of production units through the ratio of economic output and environmental impact. Atmospheric environmental efficiency provides a further focus on environmental efficiency in the field of atmospheric environment, which can reflect the comprehensive performance level of the regional atmospheric environment [21–23]. In recent years, as global air pollution prevention and control work has received wide attention from academia and society, many academics have conducted studies on the efficiency of the atmospheric environment, as shown in Table 1.

Table 1. Summary of application of Data Envelopment Analysis (DEA) in atmospheric environmental efficiency.

Author	Scope of Study	Period	Input Indicators	Desirable Output	Undesirable Output	Method
Lu et al., 2019 [22]	11 cities in Zhejiang	2006–2016	SO_2, NOx, smoke and dust emissions, total industrial exhaust emissions	GDP	IAQI	Non-radial DEA Malmquist Index
Wu and Guo, 2021 [24]	29 Chinese provinces	2012	SO_2, NOx, soot, coal consumption, car ownership, capital and labor	GDP	$PM_{2.5}$ emissions	The undesirable output DEA model
Piao et al., 2019 [25]	30 Chinese provinces	2005–2014	Employment, energy and water consumption, capital stock	GDP	CO_2, SO_2, etc.	DEA, ML productivity
Song et al., 2019 [26]	30 Chinese provinces	2004–2015	Employees, consumption of standard coal, capital stock	GDP	SO_2	meta-frontier non-radial angle DEA
Deng and Zhang, 2022 [27]	285 Chinese cities	2011–2018	Public service labor force, environmental protection investment	Green area	SO_2, smoke	SBM-DEA
Zhang et al., 2016 [28]	30 Chinese provinces	2005–2011	Labor employment, capital stock and energy consumption	GDP	CO_2, SO_2	SBM-DEA
Wang et al., 2018 [29]	Provincial thermal power industry	2006–2014	Energy consumption, installed capacity and employee	Electricity generation	CO_2, SO_2 NO_X, soot emissions	DEA-based materials balance approach
Yang and Li, 2018 [30]	39 Chinese industrial sectors	2003–2014	Capital, labor, energy consumption	Industrial value added	Industrial waste gas emissions	DEA model
Ma et al., 2021 [31]	30 Chinese provinces	2001–2018	employed persons, total energy and water consumption, capital stock,	GDP	$PM_{2.5}$ concentration	SBM-Undesirable-VRS model
Li et al., 2019 [32]	31 Chinese cities	2013–2017	Employees, fix assets and energy consumption	GDP	$PM_{2.5}$, SO_2 and NO_2	Resample SBM DEA
Wu et al. 2016 [33]	29 Chinese provinces	2000–2010	Energy, labor and fixed asset investment	GDP	$PM_{2.5}$ emissions	input-oriented ZSG-DEA model
Zhang et al., 2021 [2]	112 Chinese cities	2003–2017	Labor, energy and water consumption, fixed asset investment	GDP	$PM_{2.5}$ concentration	Super-SBM-DEA GML productivity
Li et al., 2021 [34]	260 Chinese cities	2003–2018	Labor, energy consumption, fixed asset investment	GDP	$PM_{2.5}$ concentration	Hybrid-Dynamic-DEA

Notes: GDP, gross domestic product. IAQI, urban environmental air quality index. ZSG-DEA, zero sum gains DEA model. ML productivity, the Malmquist and Luenberger productivity index.

(1) In terms of research methods, DEA is a non-parametric method that does not need to set subjective weights and process dimension data. Therefore, it has been widely used to measure atmospheric environmental efficiency [34,35]. From the traditional radial framework to the non-radial model framework considering relaxation variables, various academics have proposed the SBM-DEA model [28,31], super SBM model [2], dynamic SBM-DEA [36], Hybrid-Dynamic DEA [34] and other improved models. The limitation of the traditional DEA method is that it is difficult to analyze efficiency accurately because it does not take into account the relaxation of output factors, and it is difficult to grasp the factors that need to be considered first to improve efficiency. The subsequently improved SBM-DEA model could avoid the deviation caused by radial and angular measurements, which is favored by scholars. In the empirical estimation, the combination of static efficiency and the dynamic efficiency analysis is often adopted, and the Malmquist index and Luenberger productivity index method are frequently selected to decompose detailed driving factors, including the technical efficiency, technological progress, and scale efficiency index of dynamic efficiency [2,22,25].

(2) For evaluation indicators, to make the DEA a reasonable method to estimate atmospheric environmental efficiency, different scholars have constructed different input-output index systems for calculation. The first way is to take the air pollutant emissions (SO_2, NOx, smoke and dust, etc.) as the input indexes and GDP as the economic output index to calculate the atmospheric environment efficiency or air pollution emissions efficiency. Further, some scholars regard the air quality rate and comprehensive index of IAQI to be the direct output factor that measures environmental benefits [22,35]. However, this index system has limitations in considering the impact of conventional production factor inputs (capital and labor) on atmospheric environmental efficiency and cannot reflect the socioeconomic background differences in the study area. The second way is to take labor, capital, energy, and other production factors as input indicators, while air pollutant emissions are an undesirable output with weak disposability and introduce a directional distance function together with the desirable output (GDP) for calculation. This method can evaluate atmospheric environmental efficiency. In specific empirical research, CO_2, SO_2, NOx, smoke and dust are often regarded as the research objects of pollutants [26,27], and particulate matters smaller than 10 μm (PM_{10}) (inhalable particles with diameters that are generally less than 10 μm), while $PM_{2.5}$ are gradually being included in the undesirable output indicators [18,34].

(3) From the research on the influence mechanism of atmospheric environmental efficiency, the ordinary panel regression model and Tobit model have often been adopted [34]. To control the influence of endogenous problems on the estimation results to the largest extent, the system Gaussian mixture model (GMM) estimation, two-stage least squares approach (2SLS), panel threshold model, spatial Dubin model, mediation effect model, DID model and instrumental variable analysis can be further employed to test the robustness of the model [1,6,27]. The explained variables in the regression model are mainly static atmospheric environmental efficiency. The level of economic development and GDP are often selected as core explanatory variables. Other explanatory variables mainly include a factor endowment structure, industrial structure, scientific and technological innovation level, foreign direct investment, government environmental management ability, environmental regulation, population density, industrial enterprise scale, investment scale, etc. [34]. At present, the development of a digital economy has brought profound changes to government governance, enterprise production, and the lives of residents, which not only directly affects pollutant emissions but also plays a strong part in the environmental supervision and technical efficiency of governments and enterprises [27]. However, few studies have been conducted to analyze the effect of the digital economy's development on environmental efficiency from a theoretical and empirical perspective.

To sum up, although existing studies have made explorations around the air pollution efficiency and its influencing factors, there are still the following deficiencies: (1) for research objects, most of the existing literature dedicated to the unexpected output of atmospheric environmental efficiency is focused on conventional pollutants, such as SO_2, NOx, smoke and dust, while less attention has been paid to the variation characteristics of PMEE; (2) for the mechanism research, in the analysis of driving factors for evaluating the reduction effect of haze emissions, the main concern is the economic development level, industrial structure, etc., while systematic research on impact mechanisms, including indicators such as the digital economy and technological innovation has been lacking, and the endogenous problems of the variables themselves not fully considered; (3) for the research scale, due to the availability of data, most of the research samples in the existing literature focus on the provincial level [26], while less detailed research focuses on the driving mechanism of PMEE at the city level. Above all, this study focuses on PMEE, taking the coastal Zhejiang province as an example, discussing the measurement level and socio-economic impact mechanism of PMEE at the city level, and establishing an analytical framework with the digital economy as the core explanatory variable. Finally, relevant policy recommendations are put forward.

The technical framework and research process of this study is displayed in Figure 1.

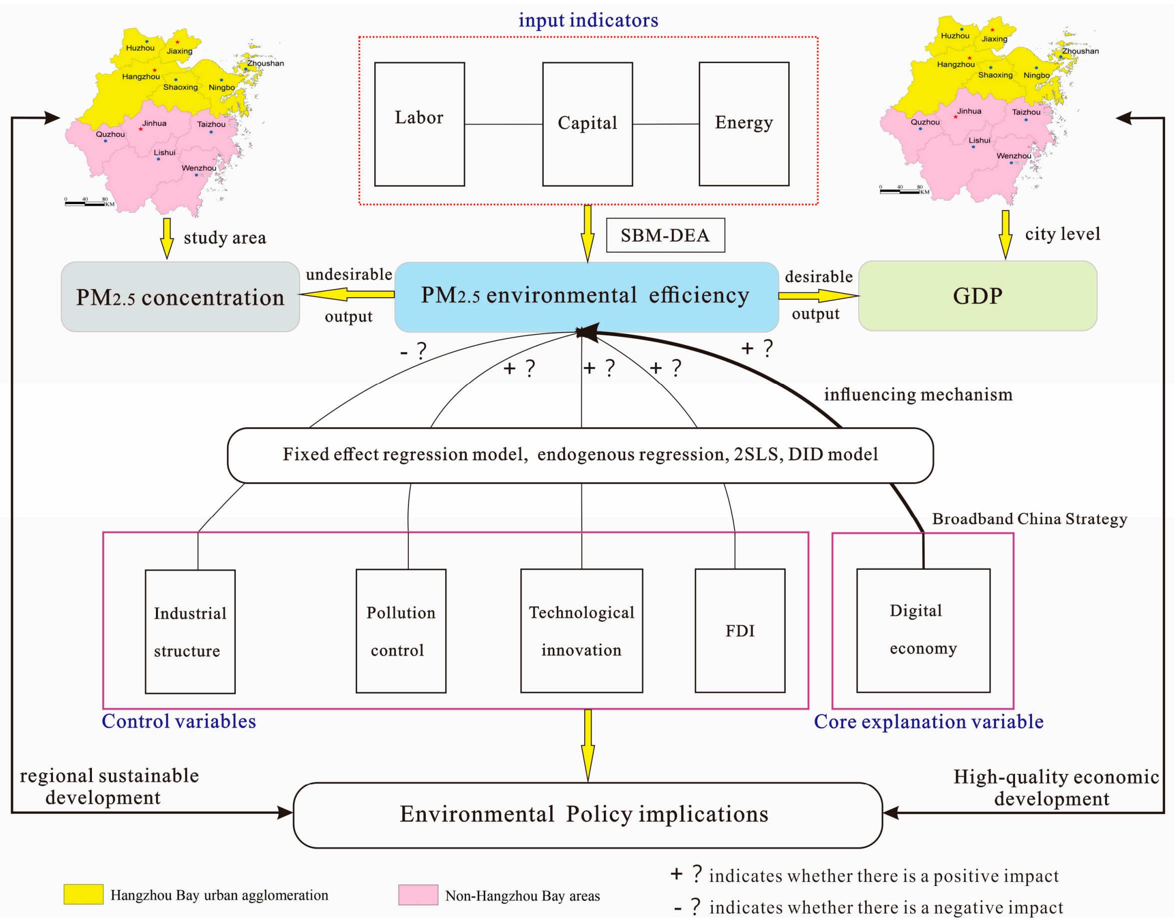

Figure 1. Technical route and analysis framework of the study.

3. Materials and Methods

3.1. Study Area

Zhejiang (Figure 2) is an economically developed province along China's eastern coast and is also one of the key areas of the Blue-Sky Protection Campaign [37–39].

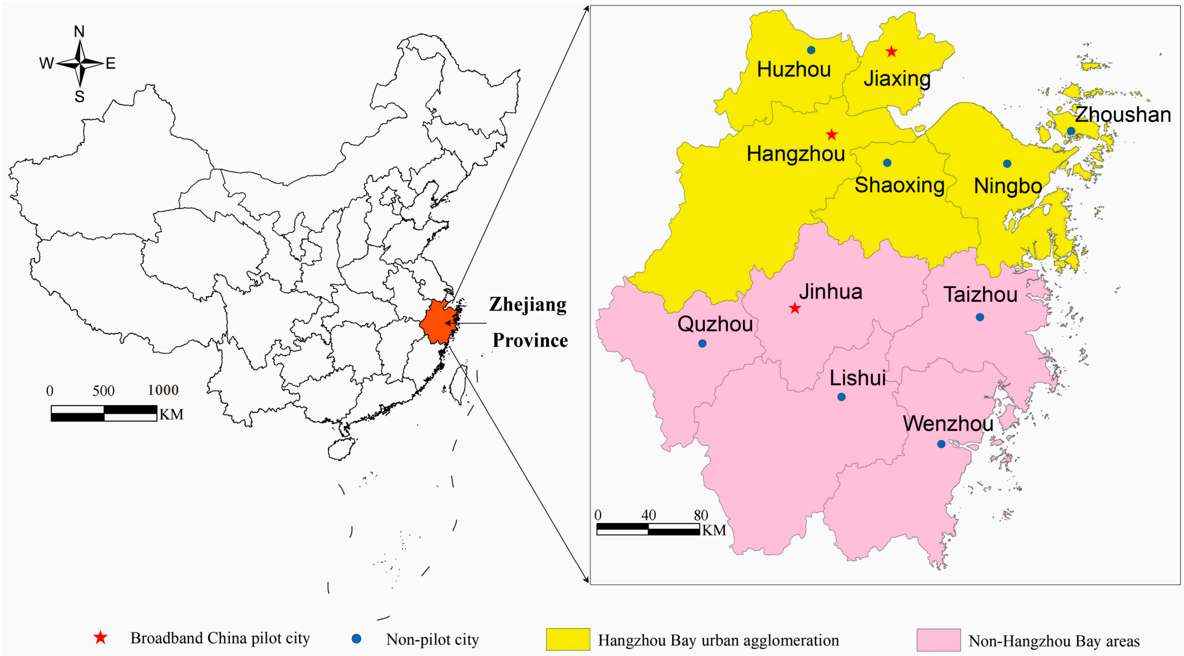

Figure 2. Map of the study area: Zhejiang province and 11 prefecture-level cities.

In 2020, the average concentration of urban $PM_{2.5}$ in Zhejiang was 25 μg/m^3, down by 43.2% compared to 2015, while the ratio of days with excellent air quality was 93.3%, an increase of 9.5% compared to 2015. Affected by the COVID-19 pandemic in 2020, along with favorable weather conditions, ambient air quality in Zhejiang has greatly improved, but the difficulty of further improvement is also increasing. In addition, a high proportion of traditional industries with high energy consumption and air pollutant emissions, such as the heavy chemical industry around Hangzhou Bay, which accounts for a relatively high proportion, and the rapid increase in production capacity has greatly offset the achievements of air pollutant emissions reduction in other industries in this region, which poses challenges to the continuous improvement of air quality [22]. In recent years, to continually optimize the industrial structure system and the environmental governance efficiency, the Zhejiang government has vigorously implemented the "No. 1 Project" of the digital economy [12]. This project has accelerated the digital, intelligent and green transformation of the traditional manufacturing industry, comprehensively promoted the industrial internet into clusters, parks and enterprises, and relies on the latest big data and artificial intelligence technologies to enhance the level of the environmental regulatory system and reduce atmospheric pollutant emissions [40,41].

It should be noted that the Hangzhou Bay urban agglomeration is an important part of the southern wing of the Yangtze River Delta world-class urban agglomeration, which is an important strategic embodiment of the comprehensive development of the region, and the linkages between the cities in terms of economic activities and environmental regulation have become closer. Hangzhou Bay urban agglomeration has led to the development of a digital economy in the whole province. Therefore, in the following analysis, we divided the 11 cities in Zhejiang into the Hangzhou Bay urban agglomeration (including Hangzhou, Jiaxing, Huzhou, Shaoxing, Ningbo and Zhoushan) and non-Hangzhou Bay areas for comparison.

3.2. Variables and Data

Referring to the existing literature [35,37], taking labor, capital and energy as input indicators, regional GDP as a desirable output indicator, and $PM_{2.5}$ with the annual average concentration as an undesirable output indicator, this study built the PMEE evaluation system in Zhejiang province, while the objective was to reduce the input of single production factors and achieve economic development and the improvement status of $PM_{2.5}$ pollution. The labor input index was expressed by the number of urban employees in each city at the end of the year [42]. The capital investment index was expressed by the investment amount of fixed assets in the whole society [32,43]. The energy input index adopted energy consumption, which was expressed by the energy consumption of industries above the designable size (10^4 tons of standard coal). The desirable output index was expressed by GDP, and the GDP of each city was converted to a constant price in 2006 to eliminate the influence of price factors [44,45]. The above indicators were obtained from the Statistical Yearbook of Zhejiang Province [46] and the Zhejiang Natural Resources and Statistical Yearbook on Environment [47] from 2007 to 2020. Linear interpolation can be used to fill in some missing data. The undesirable output was the average $PM_{2.5}$ annual concentration ($\mu g/m^3$) in each city, from the grid data of the annual mean of the global concentration of $PM_{2.5}$ based on satellite surveillance disseminated by the Socioeconomic Data and Application Center of Columbia University, with a grid resolution of $0.1° \times 0.1°$ [48]. Specifically, the grid data of the annual average $PM_{2.5}$ concentration was overlaid on the administrative boundary of the 11 cities in Zhejiang and then converted to the annual average city-wide $PM_{2.5}$ concentration data.

The descriptive statistical results of the aforementioned variables are summarized in Table 2.

Table 2. Descriptive statistics of variables from 2006 to 2019 in Zhejiang province.

Variable	Indicator	Variable Name	Sample	Mean	Standard Deviation	Min	Max
Input variable	Employed persons	Labor	154	327.43	177.90	55.84	720.00
	Energy consumption	Energy	154	987.98	687.76	83.78	3273.51
	Investment in fixed assets	Capital	154	1797.42	1484.54	210.17	7241.91
Desirable output	GDP	GDP	154	3318.48	2842.11	335.20	15,375.05
Undesirable output	$PM_{2.5}$ concentration	$PM_{2.5}$	154	48.33	12.51	20.10	70.90
Key explanatory variable	Digital economy level	De	154	0.43	0.31	0.87	0.12
Control variable	Industrial structure level	Ind	154	42.70	6.60	23.00	54.82
	Pollution control level	Reg	154	81,329.4	77,937.8	985.0	362,335.0
	Technological innovation level	Tec	154	1.72	0.71	0.21	3.29
	Foreign direct Investment level	Fdi	154	126,329.2	166189.3	1926	720,915

3.3. SBM-DEA Model with Undesirable Output

The DEA and its expanded models are widely used for efficiency measures or performance evaluations [49]. The traditional Banker, Charnes and Cooper model (BCC) and Charnes, Cooper and Rhodes model (CCR) are DEA models that evaluate performance radially and angularly [22,50]. The radial means that the same proportional input or output change is required when performing efficiency evaluation. When there is an excessive input or insufficient output, the radial DEA will overestimate the efficiency of the decision-making unit (DMU). Angular requires the selection of a model between input-based performance evaluation (assuming the output remains unchanged) or output-based performance evaluation (assuming the input remains unchanged). Therefore, changes in inputs or outputs are often ignored, and the efficiency value of DMU is overestimated [51,52]. To solve the above-mentioned problems of the traditional DEA model, Tone (2001, 2002) proposed a non-radial, non-angular DEA model based on slack variables [53,54], such as the SBM-DEA model with undesirable output. Compared with the traditional DEA model, the SBM-DEA model with undesirable output is a more rigorous efficiency evaluation method, which is not affected by index units. It not only avoids the deviation caused by radial and angular measurements but also takes into account the influence of undesirable output factors on the production process, which may better reflect the nature of efficiency evaluation. In addition, in the SBM-DEA model, each DMU minimizes the input and maximizes the output simultaneously to calculate efficiency, which brings a large clear efficiency ranking benefit [30,33,45,48].

Based on the undesirable output SBM-DEA model [36,54], we assumed that n denoted the number of DMUs, and the input variables could be computed with $X = (x_{ij}) \in R^{m\times n}$. The desirable output variable was calculated by $Y = \left(y_{kj}\right) \in R^{s_1\times n}$ while the undesirable variable was $Z = \left(z_{lj}\right) \in R^{s_2\times n}$. We assumed $X > 0$, $Y > 0$, and $Z > 0$ and that the production possibility set would be $P = \{(x,y,z) \mid x \geq X\Lambda, y \leq Y\Lambda, z \geq Z\Lambda, \Lambda > 0\}$ of which $\Lambda = (\lambda_1, \lambda_2, \ldots, \lambda_n) \in R^n$ indicates the weight coefficient vector. $x \geq X\Lambda$ in the P set denotes that the actual input was larger than the frontier input; $y \leq Y\Lambda$ in the P set denotes that the actual output was less than the frontier output. The undesirable output SBM model can be listed as follows.

$$\min\rho = \frac{1-\frac{1}{m}\sum_{i=1}^{m}\frac{s_i^x}{x_{i0}}}{1+\frac{1}{s_1+s_2}\left(\sum_{k=1}^{s_1}\frac{s_k^y}{y_{k0}}+\sum_{l=1}^{s_2}\frac{s_l^y}{y_{l0}}\right)}$$
$$s.t.\begin{cases} x_{i0} = \sum\limits_{j=1}^{n}\lambda_j x_j + s_i^x, \forall i; \\ y_{k0} = \sum\limits_{j=1}^{n}\lambda_j y_j - s_k^y, \forall k; \\ z_{l0} = \sum\limits_{j=1}^{n}\lambda_j z_j + s_l^z, \forall l; \\ s_i^x \geq 0; s_k^y \geq 0; s_l^z \geq 0; \lambda_j \geq 0; \forall i, j, k, l; \end{cases} \tag{1}$$

where $s^x \in R^m$ and $s^z \in R^{s_2}$ represent the redundancy of DMU (x_0, y_0)'s input and undesirable output; $s^y \in R^{s_1}$ refers to the shortage of a desirable output; ρ denotes the PMEE in one particular city; m refers to the number of input variables; S_1 and S_2 are the numbers of a desirable and undesirable output; λ denotes the weight matrix, and input frontier and output frontier can be obtained via a λ multiplied input and output indicator matrix [55].

Model (1) was under the assumption of constant returns to scale. Under the assumption of variable returns to scale, the constraint condition $\sum_{j=1}^{n}\lambda_j = 1$ should be added. If $\rho = 1$, $s^x = 0$, $s^y = S^z = 0$, it indicates that input redundancy and output shortage are 0 and the DMU is the most efficient. If $\rho < 1$, it indicates an excessive input, that the desirable output was insufficient, or that the undesirable output was excessive. Additionally, this indicates that the DMU was not of the highest efficiency and could be improved [22].

3.4. Econometric Regression Model

Based on empirical analysis and existing research [27,31,34,56], and taking into account data availability, PMEE in Zhejiang province was used as the dependent variable, while the level of the digital economy, industrial structure, pollution control, technological innovation and foreign direct investment were used as independent variables to investigate the impact mechanism. The five explanatory variables can be described as follows:

(1) Level of the digital economy. It is a core explanatory variable. Promoting the development of the digital economy reinforces the intensive transformation of industrial production methods through technological innovation, thereby improving the current state of $PM_{2.5}$ pollution and the $PM_{2.5}$ environmental control efficiency. Referring to the estimate of the level of development of the digital economy at the city level [18,27,57], this study comprehensively considered four dimensions of the digital economy, including digital infrastructure, digital industry, digital technology, and digital applications. Four indicators, including the proportion of internet users, the proportion of mobile phone users, the employees' proportion in the information transmission and technology service industry, and the total per capita telecommunications business, were used to build a digital economy indicator system. After standardization, the entropy method was used to estimate the indicator's weight, and the digital economy's comprehensive development index was calculated, which was denoted as *De*.

(2) Level of industrial structure. The proportion of the industrial output value in GDP was used to measure this indicator. Industrial pollution is one of the important sources of $PM_{2.5}$ emissions. This indicator affects PMEE from the perspective of source management [27,58].
(3) Level of pollution control. The yearly operating cost of industrial waste gas treatment facilities was selected to measure this indicator. It affected the PMEE from the perspective of waste treatment investment and technical capability [27].
(4) Level of scientific technological innovation. This was measured by the ratio of Research and Development funds to GDP in each city. It reflected the impact of technological investment and technological progress on PMEE [27,31].
(5) Level of FDI. The ratio of actually used FDI to GDP in each city was used to measure the level of FDI in each city. This indicator was mainly used to test the "Pollution Shelter" hypothesis and analyze its impact on the PMEE [31,37].

Therefore, the causality between PMEE and the digital economy was calculated as follows:

$$PMEE_{i,t} = \alpha_1 + \alpha_2 De_{i,t} + \beta_1 lnX_{i,t} + \mu_i + \gamma_t + \varepsilon_{i,t} \quad (2)$$

where $PMEE_{i,t}$ denotes the PMEE in city i in time t; $De_{i,t}$ denotes the digital economy level (distributed in 0–1) in city i in time t; $X_{i,t}$ denotes the vector of all the control variables, and, in order to eliminate the difference in units of variables, logarithmic processing was conducted here; μ_i denotes the fixed individual effect with the aim of controlling the individual differences between cities; γ denotes the fixed time effect with the aim of eliminating the time trend; $\varepsilon_{i,t}$ denotes random disturbance; α_1 denotes the constant; α_2 denotes the coefficient of the digital economy. If the coefficient α_2 is still significantly positive after the control of the above-mentioned control variables, the digital economy could contribute to the improvement of PMEE.

Compared with the existing literature [20,31], the empirical model in this study had the following distributions. (1) The indicator of the economic development level (GDP) was not included in the regression model because when the DEA efficiency was decomposed, the GDP indicator was used as one indicator of a desirable output. If the GDP were readopted to explain the PMEE, it might increase the endogenous problem of the model. (2) The digital economy level was added to the econometric model. The regional digital economy level reflected the government's effective use of resource allocation and the production efficiency of enterprises. This indicator could reflect the impact of the technical efficiency of $PM_{2.5}$, which ensured the precision of the regression model.

4. Results

4.1. Regional Difference of $PM_{2.5}$ Concentration in Zhejiang

The spatial distribution of the $PM_{2.5}$ concentration in 11 prefecture-level cities in Zhejiang from 2006 to 2019 is demonstrated in Figure 3. For comparison, this study chose four different years from different time periods, which were 2006 (the starting year of China's 11th Five-Year Plan), 2011 (the starting year of China's 12th Five-Year Plan), 2016 (the starting year of China's 13th Five-Year Plan), and 2019 (the end year of this study).

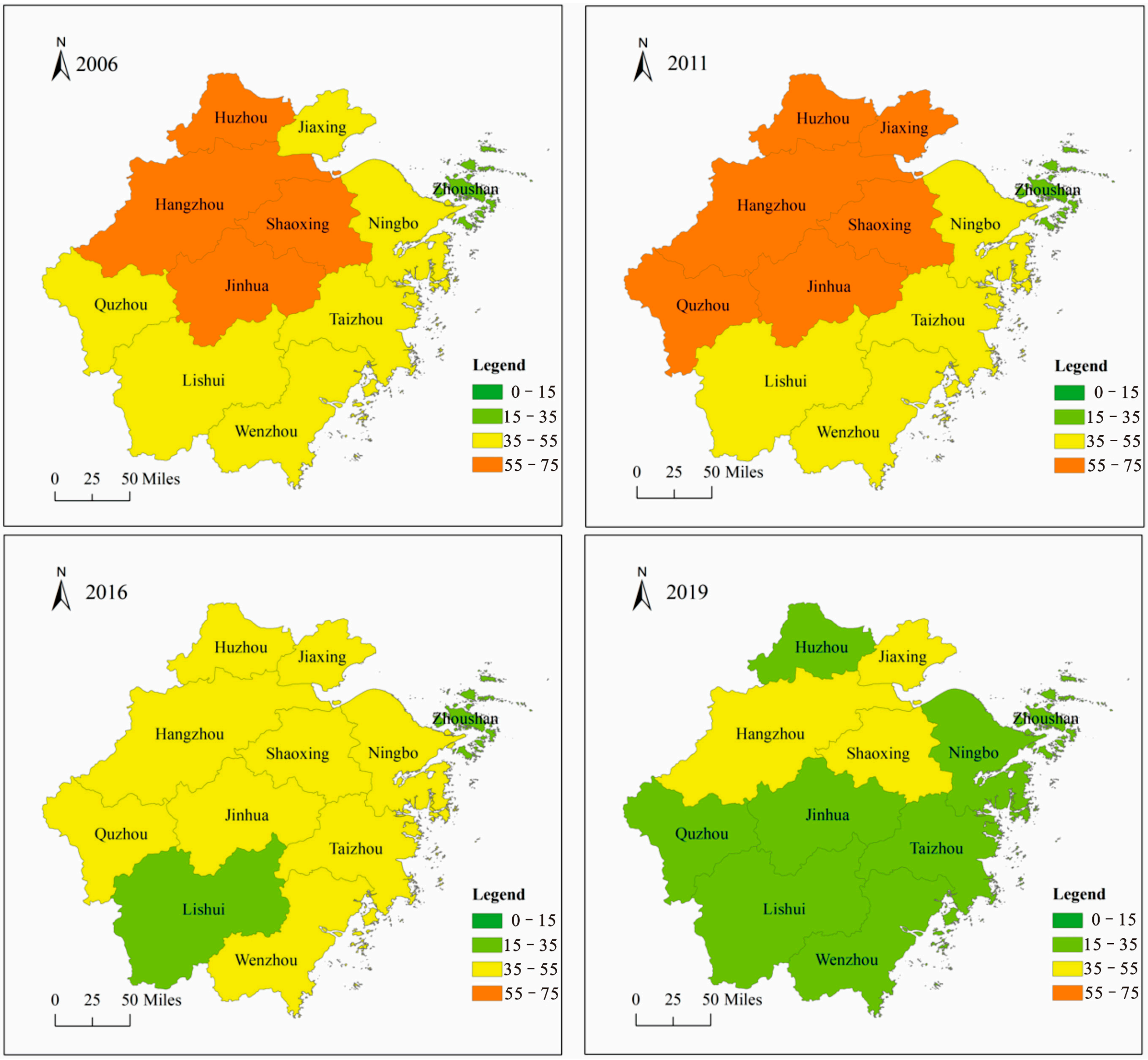

Figure 3. Spatial distribution of $PM_{2.5}$ concentration in Zhejiang province from 2006 to 2019 (unit: $\mu g/m^3$).

The $PM_{2.5}$ concentration of Zhejiang was characterized by a continuous reduction in concentration and the continuous improvement in environmental quality. In 2006, only Zhoushan reached the national Class II ambient air quality (35 $\mu g/m^3$), which was 29.2 $\mu g/m^3$. By 2019, eight cities reached the national Cass II ambient air quality standard. Only Hangzhou, Jiaxing and Shaoxing did not reach the Class II standard, but none of these 11 cities reached the national Class I ambient air quality standard (15 $\mu g/m^3$). The ranking of the average $PM_{2.5}$ concentration for 2006–2019 was Shaoxing > Hangzhou > Jinhua > Huzhou > Jiaxing > Quzhou > Wenzhou > Ningbo > Taizhou > Lishui > Zhoushan. The $PM_{2.5}$ concentration in Zhoushan was the lowest. This was mainly due to the development of tourism and fisheries, which had a lower proportion of pollution-intensive industries and lower emissions of air pollutants [33]. Subsequently, Zhoushan is an island-type city with strong sea-to-land winds; the frequent exchange of land and sea winds at Zhoushan makes its airflow and pollutant dispersal fine and the ability of self-purification strong. Thus, Zhoushan had the lowest $PM_{2.5}$ pollution. Lishui began to meet the national Class II ambient air quality after 2016. Overall, the concentration of $PM_{2.5}$ in the urban agglomeration around Hangzhou Bay was more serious than that in non-Hangzhou Bay areas.

4.2. Analysis of PMEE in Zhejiang

Through the aforementioned SBM-DEA model with an undesirable output, the PMEE of 11 cities in Zhejiang was calculated by Equation (1). The specific results are presented in Table 3 and Figure 4.

Table 3. Results of PMEE in 11 cities in Zhejiang province from 2006 to 2019.

Regions	City	2006	2011	2016	2019	14-Year Average	Rank
Hangzhou Bay urban agglomeration	Hangzhou	0.6302	0.5082	0.7037	1.000	0.7180	2
	Ningbo	0.4303	0.6809	1.000	1.000	0.7175	3
	Jiaxing	0.4064	0.4134	0.4618	0.5950	0.4534	11
	Huzhou	0.4266	0.4368	0.5103	0.6578	0.4952	9
	Shaoxing	0.5117	0.4746	0.5574	0.6519	0.6119	8
	Zhoushan	1.0000	0.9316	0.8404	1.0000	0.9387	1
Non-Hangzhou Bay areas	Wenzhou	0.7375	0.5020	0.4879	0.6980	0.6479	7
	Jinhua	0.5579	0.6657	0.5762	0.7288	0.6522	6
	Quzhou	0.4288	0.4539	0.4787	0.5636	0.4704	10
	Taizhou	0.6110	0.5919	0.5131	0.6710	0.6662	5
	Lishui	0.5325	0.7773	0.6436	1.0000	0.7021	4
Total average		0.5702	0.6445	0.6293	0.7787	0.6430	

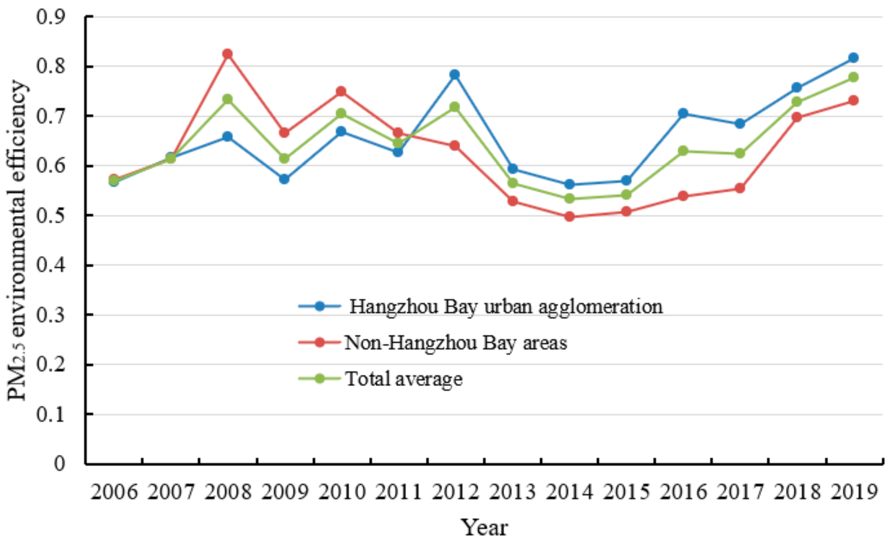

Figure 4. Comparison of PMEE in different regions of Zhejiang province.

Over the past 14 years, the average PMEE value for the entire Zhejiang province has been 0.6430, and there was an opportunity for an improvement of about 36% from the production frontiers. There was still great potential for improving and controlling the PMEE. In terms of the overall PMEE in each city, it showed a certain trend of fluctuating growth. In 2019, four cities (Hangzhou, Ningbo, Zhoushan and Lishui) reached the production frontiers, while the remaining seven cities did not reach the $PM_{2.5}$ emission reduction technology of the common frontier cities, which meant that these cities still had a certain potential to improve the PMEE. It also revealed that there were some regional differences in PMEE among different cities. From the 14-year average PMEE of each city, the PMEE of 11 cities ranked as Zhoushan > Hangzhou > Ningbo > Lishui > Taizhou > Jinhua > Wenzhou > Shaoxing > Huzhou > Quzhou > Jiaxing. Due to variations in different years, the ranking of PMEE in different cities also changed considerably. The cities with high PMEE values were mainly Zhoushan, Hangzhou and Ningbo, while the cities with low PMEE were mainly Huzhou, Quzhou and Jiaxing. Among them, Hangzhou and Ningbo were the two most developed cities in Zhejiang in terms of economy and technology. Since the 13th Five-Year Plan, relying on continuous technological innovation, the two cities' key polluting industries were technologically transformed and controlled at the end of the treatment period [22,37], effectively reducing air pollutant emissions such as nitrogen oxide and particulate matter and effectively enhancing the PMEE.

Further, Zhejiang province was divided into Hangzhou Bay urban agglomeration and non-Hangzhou Bay areas for comparison (Figure 4). The results show that the PMEE of the Hangzhou Bay urban agglomeration increased from 0.5675 in 2006 to 0.8174 in 2019, with a growth rate of 44.03%. The PMEE in non-Hangzhou Bay areas rose from 0.5735 in 2006 to 0.7323 in 2019, with a growth rate of 27.69%. At the same time, from 2006 to 2011, the PMEE of the non-Hangzhou Bay area was higher than that of the Hangzhou Bay urban agglomeration. At this stage, the air pollutant emissions and $PM_{2.5}$ concentrations from Hangzhou Bay urban agglomeration were higher, and the emission reduction pressure was higher. After 2012, the PMEE of Hangzhou Bay urban agglomeration was significantly higher than that of non-Hangzhou Bay areas, so the PMEE of the entire province had a stable growth trend. This resulted from the fact that, after the 12th Five-Year Plan to improve the ambient air quality effectively and strive to build a beautiful Zhejiang, the provincial government increased investment in addressing $PM_{2.5}$ pollution, accelerated the adjustment of industrial structure and energy structure relying on scientific and technological innovations [22,37], and improved PMEE effectively, especially in Hangzhou, Ningbo, Zhoushan and other cities around Hangzhou Bay. After 2012 (when $PM_{2.5}$ was included in the national key control object of air pollution prevention and control), Zhejiang successively issued and implemented the 13th Five-Year plan for air pollution prevention and control of Zhejiang Province (2016–2020) (2017) and the 14th Five-Year plan for air quality improvement of Zhejiang Province (2021–2025) (2021). Especially after 2016, the provincial government implemented extensive air pollution prevention and persistent control measures, which were deployed to high standards, promoted the success of the Blue-Sky Protection Campaign [41], and innovated the construction of fresh air demonstration areas (a key assessment index is $PM_{2.5}$ concentration). Thus, the PMEE in the entire province was obviously improved.

4.3. Influencing Factors of $PM_{2.5}$ Environmental Efficiency

4.3.1. Benchmark Regression Results

The fixed-effect model is able to overcome the errors caused by missing variables. This study employed the fixed effect for benchmark regression estimations (Table 4) and the method of gradually increasing control variables to estimate column (1). To eliminate the individual fixed effect and time trend of the city, the dummy variables reflecting individual city characteristics and the yearly dummy variables reflecting temporal characteristics were added to the model. The results of the regression estimation of the two-way fixed effect model illustrated that the impact coefficient of the development level of the digital economy on urban PMEE was 0.932, with a positive significant level at 1%, showing that the development level of the urban digital economy significantly promoted an improvement in PMEE, which was in line with theoretical expectations. The results of columns (2)–(5) displayed a significant positive correlation between the level of development in the digital economy and PMEE, which still existed after the control variables were added. $PM_{2.5}$ emissions could be reduced effectively by digital economy development through green innovation and the optimization of resource allocation. Previous studies have also illustrated that improving digital economy development could promote the intensive industrial transformation production mode by enabling technological innovation to combat the current situation of environmental pollution [27]. With the economic society of Zhejiang entering the digital era, the proportion of the digital economy in the total economic volume is expanding year by year, and Zhejiang has become fertile soil for achieving regional high-quality innovation and sustainable development. Firstly, the digital economy improves the efficiency of resource distribution and decreases air pollutant emissions from inefficient production. Another important aspect is that the integrative development of the digital economy and real economy promotes innovation output and efficiency and reduces innovation costs. As a consequence, digital economy development has become an important solution to atmospheric environmental problems [59].

Table 4. Benchmark regression estimation results.

Variables	(1) PMEE	(2) PMEE	(3) PMEE	(4) PMEE	(5) PMEE
lnDe	0.932 *** (3.731)	0.947 *** (3.835)	0.835 *** (3.429)	0.846 *** (3.501)	0.908 *** (2.537)
lnInd		−0.043 ** (1.362)	−0.055** (1.279)	−0.048 ** (1.318)	−0.052 ** (1.294)
lnReg			0.142 *** (0.921)	0.133 *** (0.844)	0.107 *** (0.832)
lnTec				0.065 ** (0.736)	0.058 ** (0.694)
lnFdi					−0.052 (0.481)
Constant	−8.593 *** (−5.621)	−7.548 *** (−4.342)	−5.361 ** (−3.107)	−4.781 ** (−2.329)	−9.382 *** (−6.218)
Urban fixed effect	Yes	Yes	Yes	Yes	Yes
Time fixed effect	Yes	Yes	Yes	Yes	Yes
R^2	0.642	0.663	0.675	0.741	0.694
Number of samples	154	154	154	154	154
Number of cities	11	11	11	11	11

Note: **, *** denoted significance level of 5%, and 1%, respectively. The above model adopted the clustering standard error, and the number in brackets is the *t* value.

From the regression results of the control variables, (1) the increase in the share of the industrial output value had a significant negative effect on the improvement in PMEE. This was primarily because the fossil energy consumption of industrial enterprises was closely related to $PM_{2.5}$ emissions. Thus, reducing the proportion of high energy-consuming industrial sectors such as steel and cement and optimizing the industrial structure could benefit the efficiency of $PM_{2.5}$ environmental governance. (2) The improvement in pollution control level took an obvious positive effect on PMEE improvement. Improving industrial exhaust gas treatment plants and end treatment technologies could effectively reduce relevant waste gas emissions. (3) The improvement of scientific and technological innovation levels had a significant positive effect on PMEE improvement, which was significant at the 5% level. The increase in enterprise research and development (R&D) investment could promote the technological upgrading of production equipment and the output of new products and then eliminate traditional production lines with high pollution emissions. (4) There was no significant impact between the level of foreign investment and PMEE, indicating that the production process and technology of foreign-invested industries in Zhejiang did not significantly improve the fight against $PM_{2.5}$ pollution, so the hypothesis of "Pollution Shelter" was not tenable here. Considering that Zhejiang is a major foreign trade province, in the future, it should closely combine the influx of foreign capital and local enterprises in technological innovation and the transformation and upgrading of production processes to control the output of pollutants at the source.

4.3.2. Endogenous Regression Results

To control the impact of endogenous problems on the estimation results to the largest extent, most of the existing literature used a dynamic panel data model or system moment estimation to alleviate the endogenous issues, but a more efficient instrumental variable method needs to be employed instead of using only the system matrix estimation method [20,27]. Therefore, the following strategies were employed. Firstly, as the proxy index of PMEE, $PM_{2.5}$ concentration was used to solve the potential measurement error problem. Generally, the lower the concentration of $PM_{2.5}$ in a city, the higher the PMEE. Secondly, the lag period of the core explanatory variable was used as its instrumental variable to alleviate the endogenous problem. The corresponding estimated results are demonstrated in Table 5.

Table 5. Endogenous estimation results.

Variables	(6) $\ln PM_{2.5}$	(7) PMEE	First Stage of 2SLS lnDe	Second Stage of 2SLS (8) PMEE
lnDe	−0.451 *** (−1.028)	0.914 *** (2.032)		1.038 *** (7.841)
L. $\ln PM_{2.5}$	0.051 *** (1.424)			
L. PME		0.231 *** (4.782)	0.175 *** (3.951)	
Controls	Yes	Yes	Yes	Yes
Urban fixed effect	Yes	Yes	Yes	Yes
Time fixed effect	Yes	Yes	Yes	Yes
R^2	0.583	0.728	0.622	0.498
Number of samples	154	154	154	154
Number of cities	11	11	11	11

Note: *** denoted the significance level of 1%. The above model adopted the clustering standard error, and the number in brackets is the *t* value.

Column (6) uses the logarithm of $PM_{2.5}$ concentration as the explaining variable for estimation. The development of the digital economy had a negative impact on $PM_{2.5}$ concentration, which was significant at the level of 1%. Thus, the digital economy could inhibit $PM_{2.5}$ emission reduction and improve air quality, which is in line with the results issued by Li et al. [20]. Column (7) represents the systematic GMM Estimation with the lag period of the core explanatory variable as the instrumental variable [60]. It indicates that the coefficient for estimating the level of development of the digital economy was significantly positive at the 1% level. Column (8) presents 2SLS estimation using the lag phase of the core explanatory variable as the instrumental variable. It illustrates that at the first stage of regression, the coefficient of the instrumental variable was significantly positive, while the Anderson LM test was significant at the 1% level, and the *F* statistic value of the weak instrumental variable test was 20.56, which is larger than the empirical value of 10. It indicates that it was reasonable to select this instrumental variable [61]. Compared with columns (8) and (7), the estimated coefficient of the development level of the digital economy exceeds the significance test of 1%. It shows that the above estimation results were robust. This means that, with the digital economy's increasing development, the application of new technologies, such as artificial intelligence, big data, and blockchain, provided technical support for government environmental regulation and enterprise production could be implemented. The continually improved environmental monitoring system provides data and a support platform for environmental governance and enhances the accuracy and effectiveness of $PM_{2.5}$ governance.

4.3.3. Exogenous Impact Test

To further overcome the possible reverse causality problem, referring to relevant studies [20,62], this study adopted the network infrastructure upgrading of the "Broadband China" pilot as the proxy for exogenous policy impact and used the DID method to evaluate the digital economy's impact on the PMEE. The Chinese government selected 120 cities (clusters) as the demonstration plots of the "Broadband China" strategy in three batches in 2014, 2015, and 2016. Jinhua, Jiaxing and Hangzhou in Zhejiang were involved, and the digital economy development was inseparable from the support of network infrastructure. The "Broadband China" strategy pilot provided a quasi-natural experience to explore the pollution reduction effect of the digital economy [27].

A multi-period double difference model with the following formula was built:

$$PMEE_{i,t} = \alpha_1 + \alpha_2 Policy + \beta_1 lnX_{i,t} + \mu_i + \gamma_t + \varepsilon_{i,t} \quad (3)$$

where *Policy* is a dummy variable for the policies of the "Broadband China" policy, indicating whether city *i* is a pilot city of "Broadband China" in year *t*. If yes, the value of the dummy variable was 1; otherwise, it was 0. Other variables were consistent with Equation (2).

Meeting the hypothesis of the parallel trend was one of the basic conditions for establishing the multi-stage DID method, which is in line with the method of Ren et al. [63] and Jacobson et al. [64] and was tested by the event analysis method. Specifically, taking the implementation time of "Broadband China" as the base year, DID estimation was performed for the dummy variables of each year before and after the implementation of the policy. Figure 5 shows the estimated results of the dummy variable (*Policy*) coefficient under the 95% confidence interval.

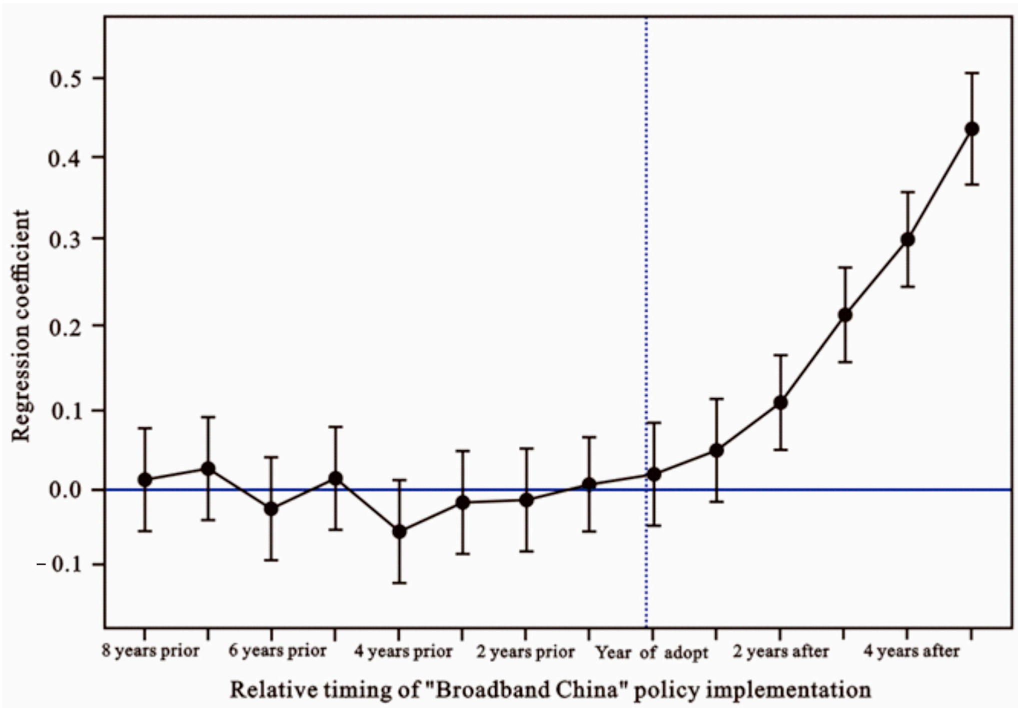

Figure 5. Estimation results of the dummy variable's parallel trend test.

In the eight years before the pilot started, the coefficient of the dummy variable fluctuated around 0 insignificantly. This means that, before the implementation of "Broadband China" in Zhejiang, there was no significant difference in the changing trend of PMEE between the pilot cities and non-pilot cities, which is consistent with the parallel trend assumption. After the pilot began, especially after Hangzhou became a pilot city in 2016, the coefficient value of the dummy variable was significantly positive, and the positive coefficient value increased, indicating that the PMEE of the "Broadband China" pilot tended to increase. Afterward, the DID method was used to estimate the average treatment effect of the "Broadband China" pilot on the PMEE of Zhejiang. The regression model estimation results are shown in Table 6. As a reference, the impact of the "Broadband China" pilot on the $PM_{2.5}$ concentration in Zhejiang was added. It was found that the impact coefficient of the "Broadband China" dummy variable on the PMEE of Zhejiang was significantly positive, while the impact coefficient on the $PM_{2.5}$ concentration was significantly negative. It also meant that the urban digital economy development represented by the implementation of the pilot policy had not only reduced $PM_{2.5}$ emissions but also improved the level of PMEE, which confirmed the stability of the empirical results.

Table 6. Double-difference estimation results of PMEE of "Broadband China" strategy in Zhejiang pilot cities.

Variables	(9) PMEE	(10) PMEE	(11) ln$PM_{2.5}$	(12) ln$PM_{2.5}$
Policy	0.294 ***	0.251 ***	−0.359 ***	−0.304 ***
	(0.472)	(0.148)	(−0.241)	(−0.172)
Constant	−2.813 ***	−2.454 ***	4.216 ***	3.892 ***
	(−1.458)	(−1.029)	(1.382)	(0.722)
Controls	No	Yes	No	Yes
Urban fixed effect	Yes	Yes	Yes	Yes
Time fixed effect	Yes	Yes	Yes	Yes
R^2	0.459	0.508	0.421	0.466
Number of samples	154	154	154	154
Number of cities	11	11	11	11

Note: *** denoted the significance level of 1%. The above model adopted the clustering standard error, and the number in brackets is the *t* value.

5. Discussion and Policy Implications

5.1. The Influence Mechanism of Digital Economy on PMEE

Through the above regression analysis and exogenous impact test, the development of the digital economy could improve the level of PMEE and produce certain emission reduction effects on $PM_{2.5}$ concentration. Compared with the existing research results [20,27], we have seen the positive effect of the development of an urban digital economy represented by the implementation of pilot policies such as "Broadband China" on PMEE. The two pilot cities, Hangzhou and Jiaxing in Zhejiang, belonged to the Hangzhou Bay urban agglomeration, which was relatively better developed in the digital economy.

As regards the specific path of influence, the improvement in the level of pollution control and the level of scientific and technological innovation had a significantly positive effect on the improvement of PMEE. These two factors may be the two major ways in which the development of the digital economy can affect PMEE. Therefore, the digital economy should first promote an improvement in industrial waste gas treatment facilities and end-treatment technologies to effectively reduce particulate matter emissions. In terms of building an enterprise green production mode, enterprises, as the main part for pollution prevention and control, can rely on technical support from virtual reality, databases, the Internet of Things and other technologies, to effectively integrate diverse information resources in production decision-making and alleviate information fragmentation and asymmetry issues in data collection and development. In this way, data on products, processes, and resources can be analyzed, decided upon, planned and reorganized to realize the efficient promotion of the production process and improve the productivity of enterprises [58,63]. Then, polluting enterprises could make full use of digital platforms to obtain information linked to technological innovation, develop cleaner production methods, optimize production processes, and actively realize the digital transformation of enterprises and reduce particulate matter emissions.

5.2. Regional Differences in $PM_{2.5}$ Environmental Efficiency Promotion

Previous studies have pointed out that different cities have different levels of $PM_{2.5}$ pollution and PMEE. Therefore, different cities need to adopt differentiated governance strategies based on their own realities.

First of all, it should strengthen the measures of zoning governance, especially for the Hangzhou Bay urban agglomeration. Taking the overall average value of the province-wide $PM_{2.5}$ concentration with PMEE as the boundary, meaning that those above the average value were recorded as H and those below the average value were recorded as L. The advantages and disadvantages of $PM_{2.5}$ pollution performance in 11 cities in Zhejiang can be classified into the following four types (see Figure 6): Type I, High pollution High efficiency, i.e., urban $PM_{2.5}$ pollution was relatively severe, but the value of PMEE was high. Type II, Low pollution High efficiency, i.e., with light urban $PM_{2.5}$ pollution and high PMEE, which was the state that achieved the best performance in the atmospheric environment. Type III, Low pollution Low efficiency, i.e., urban $PM_{2.5}$ pollution was relatively low, while the PMEE was also low. Type IV, High pollution Low efficiency, i.e., urban $PM_{2.5}$ pollution was relatively serious, and the PMEE was also low, which was the worst state for the performance of the atmospheric environment.

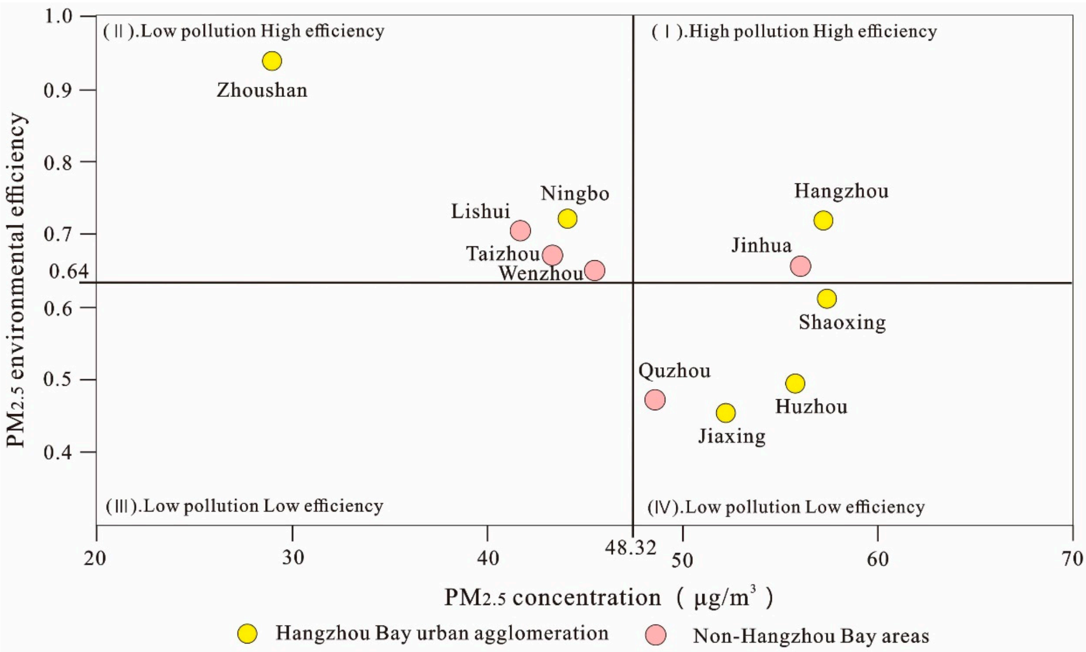

Figure 6. High and low classification of $PM_{2.5}$ control performance in Zhejiang province.

As seen in Figure 6, there were two Type I cities, namely Hangzhou and Jinhua, which were also the pilot cities of the "Broadband China" strategy. The number of Type II cities was the greatest, with five cities including Zhoushan, Lishui, Ningbo, Wenzhou, and Taizhou. There was no Type III city. There were four cities belonging to Type IV, namely Quzhou, Shaoxing, Jinhua, and Huzhou. The primary task for Type I and IV cities was to reduce $PM_{2.5}$ emissions and $PM_{2.5}$ concentration in the process of economic development. Type IV cities could also cooperate to improve the efficiency of $PM_{2.5}$ governance. Cities in Type II needed to maintain the current development trend and reflect the $PM_{2.5}$ environmental governance efficiency while reducing air pollutant emissions.

In addition, Hangzhou, Ningbo, and other digital economy-developed cities should encourage enterprises to invest in green technology research and development and could play a role in the spillover effect of technology to stimulate the enhancement of PMEE in Huzhou, Shaoxing, Quzhou, and other cities. In addition, cities with low PMEE need to strengthen technology introduction or technological transformation further and moderately increase the pressure on environmental assessments such as energy conservation and emissions reduction.

5.3. Other Necessary Policy Recommendations

For other regions confronted with environmental governance and high-quality economic development, the following suggestions are proposed:

The digital economy plays an indispensable role in integrating various information resources in the production of decision-making, alleviating information fragmentation and asymmetry in data collection and development.

1. It is necessary to accelerate the development of the digital economy and improve the efficiency of government pollution control. The digital economy can effectively integrate all kinds of information resources in production decision-making, alleviate information fragmentation and asymmetry issues in data collection and development,

and conduct decisional analysis and reorganize product data, process data, and resource data. Therefore, it can realize the efficient promotion of the production process, improve the productivity of enterprises, and support PMEE improvement by reducing resource waste and pollutant emissions.

2. It is necessary to implement precise pollution control and improve the technical efficiency of $PM_{2.5}$ treatment. Environmental digital management can be taken as a means to highlight $PM_{2.5}$-governance in key areas, key periods, key fields, and key industries and promote the in-depth governance of volatile organic compounds in petrochemical, chemical, industrial coating, and other industries [65]. Relying on the continually advanced environmental data monitoring network, the ability to provide an early warning, the perception of pollution sources, and the ability of government environmental supervision can be improved. The level of $PM_{2.5}$ pollution control can be upgraded by improving the accuracy and effectiveness of government environmental supervision.
3. It is vital to rely on innovation and technological progress to accelerate industrial transformation and upgrading. The methods include increasing investment in research and development funds in air pollution prevention and control technology, encouraging industrial enterprises to develop low-carbon and green technologies, promoting technological change in the field of energy and the environment, as well as reducing fossil energy consumption and pollution emissions at the source. Moreover, traditional industries can be phased out and replaced by green environmental protection industries, and the emission intensity of atmospheric pollutants in traditional manufacturing sectors will be gradually reduced. Future areas of industrial development include clean energy vehicles, cloud computing, big data, 5G, medical installations, and aviation and satellite applications.

6. Conclusions

Based on the concentration of $PM_{2.5}$ and the relevant socio-economic indicators of 11 cities in Zhejiang province from 2006 to 2019, this study first measured PMEE by adopting the unexpected output SBM-DEA model. Then, the impact of the digital economy on the PMEE and its internal mechanism was empirically tested by using multi-dimensional empirical methods. The conclusions are as follows:

(1) During the study period, the $PM_{2.5}$ pattern of Zhejiang province indicated the characteristics of a continuous reduction in the concentration and continuous improvement in environmental quality. $PM_{2.5}$ pollution was relatively serious in Hangzhou, Jiaxing, Shaoxing and other cities around Hangzhou Bay.

(2) The average value of PMEE in Zhejiang province was 0.6430, and there was about a 36% possibility for improvement in production frontiers, and the PMEE of each city showed a certain fluctuating growth trend. The cities with high PMEE were mainly Zhoushan, Hangzhou, and Ningbo.

(3) The results of benchmark regression and endogenous regression estimation indicated that the development level of the digital economy had a crucial effect on promoting urban PMEE. At the same time, the level of pollution control and scientific and technological innovation also had a significantly positive impact. By contrast, the proportion of the industrial output value had a certain negative effect on PMEE. The positive impact of the development of the digital economy on urban PMEE was still tenable after the robustness test through the use of methods that replaced explanatory variables. The results of the exogenous impact test indicated that the development of the urban digital economy, represented by the implementation of a pilot policy, not only reduced $PM_{2.5}$ emissions but also improved the level of PMEE governance. This means that the results of the empirical analysis were reliable.

Limited by the availability of the sample data, the research area of this paper focused on Zhejiang: a typical province on the eastern coast of China. With the continuous development of artificial intelligence, blockchain technology, and digital economy, as well as the improvement of relevant indicators, researchers should continue to expand the scope and samples of the research area and explore the driving mechanism and internal transmission mechanism of the digital economy on PMEE and air pollution further in the future.

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Abbreviations

$PM_{2.5}$	fine particulate matter smaller than 2.5 μm
PM_{10}	particulate matter smaller than 10 μm
PMEE	$PM_{2.5}$ environmental efficiency
GDP	Gross domestic product
DEA	Data Envelopment Analysis
SBM	Slack-Based Measure
ZSG-DEA	Zero sum gains DEA model
DID	Difference-in-differences
IAQI	Urban environmental air quality index
R&D	Research and development
DMU	Decision-making unit
CCR	Charnes, Cooper, and Rhodes
BCC	Banker, Charnes and Cooper
FDI	Foreign direct investment level

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