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Carbon Emission Efficiency and Reduction Potential Based on Three-Stage Slacks-Based Measure with Data Envelopment Analysis and Malmquist at the City Scale in Fujian Province, China

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Abstract: Increased carbon emissions led to extreme weather, global warming, and other environmental problems. In order to control energy input and reduce carbon emissions, this study first combines a three-stage Slacks-Based Measure with Data Envelopment Analysis (SBM-DEA) and uses the Malmquist index to quantify energy consumption at the city scale and the related carbon emission efficiency in Fujian Province for the period 2015–2020. Second, we explore the carbon reduction potential on the city scale from the perspective of improving carbon emission efficiency. Our results demonstrate that (i) the carbon emission efficiency of the nine cities increases overall in the first stage, when technical efficiency approaches the efficiency frontier state and efficiency shortage is mainly caused by the lack of pure technical efficiency. (ii) Regression by stochastic frontier analysis in the second stage reveals that the secondary industry correlates positively at 1% significance with fossil energy consumption and power consumption, indicating that the carbon emission efficiency decreases as the secondary industry increases. (iii) Putian and Xiamen reduced their carbon emission efficiency in the third stage due to (a) the input redundancy of fossil energy and social power consumption and (b) excessive undesirable output carbon emissions. (iv) There were improvements in carbon emission efficiency peaks in 2015, with Longyan, Ningde, and Sanming improving by about 50%. This improvement then decreased up to the year 2020, when the improvement in the carbon emission efficiency of Ningde and Zhangzhou was 6.02% and 9.50%, respectively, and that of all other cities was less than 1%. Therefore, we suggest that carbon emission reduction in the future can be further improved by improving technology, optimizing industrial structure, and various other ways to further improve carbon emission efficiency.

Keywords: SBM-DEA; Malmquist; carbon emission efficiency; potential in carbon reduction; carbon emission

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1. Introduction

Taking action to combat climate change and reduce human carbon emissions is an important means to achieve green, low-carbon, and sustainable development. Since the Industrial Revolution, carbon emissions from human activities have increased exponentially, disrupting the carbon dioxide (CO_2) balance of the biosphere and causing a series of ecological problems, such as the greenhouse effect, acid rain, and extreme weather [1,2]. According to the Sixth Assessment Report of the United Nations Intergovernmental Panel on Climate Change (IPCC) of Working Groups I and III [3], human activity is the root cause of global warming. Restricting global warming requires a major transformation of the energy sector and achieving "carbon neutrality" as soon as possible is the only way to address climate change. Achieving carbon neutrality requires numerous technological innovations. Although the overall carbon emissions of Fujian Province are not high, differences exist between its cities, and coastal and inland regions are developing at different rates. Measuring the carbon emission efficiency of different regions helps to target reduction in emissions in cities [4,5], optimize the measures for reducing carbon emissions, and control carbon emissions at their root.

Fujian Province is the first ecological civilization pilot zone with significant ecological advantages in the southeast of China. According to previous research, Fujian Province is one of the benchmark provinces for green and low-carbon economic transformation [6] and has a small base for total carbon emissions and low carbon emission intensity, both of which are in the middle range for China. Therefore, it is particularly important to bring the goal of carbon peaking and carbon neutrality into the construction layout of the ecological province. At present, Fujian Province is experiencing rapid economic and social development, with abundant opportunities for economic and social development. However, the energy structure is more coal and industrial structure, especially as the average annual energy consumption of industrial sectors accounts for more than 60%, as the gap between carbon emission efficiency and the production frontier means that there is carbon reduction potential [7]. Therefore, the comprehensive carbon emission efficiency directly affects the ecological protection and green development of Fujian Province. Currently, Fuzhou, Quanzhou, Zhangzhou, Xiamen, Sanming, Longyan, Putian, Nanping, Ningde, and Pingtan Comprehensive Experimental Zone are under the administration of Fujian Province. Considering that the carbon emissions of Pintan Comprehensive Experimental Zone are extreme low, this paper excludes Pingtan and selects nine cities of Fujian Province as the research object to study the carbon emission efficiency and carbon reduction potential in these regions. See Figure 1.

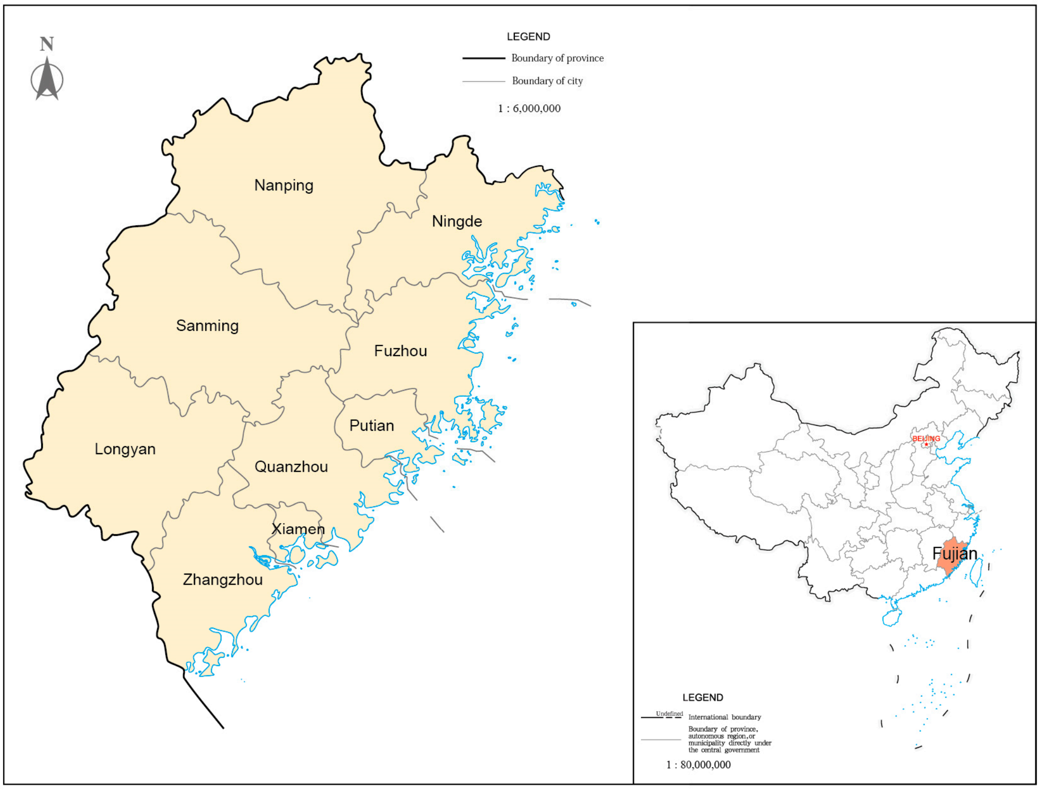

Figure 1. The location of Fujian province in China.

This study uses the emission factor method and the model provided in the Guide to Provincial Greenhouse Gas Inventories (Trial) to quantify the energy-consumption-related carbon emissions of Fujian Province from 2015 to 2020. Fuzhou is the capital of Fujian Province and its total GDP in 2020 ranks second in the province. The carbon emissions of Fuzhou have been the second highest in the province since 2015, and the carbon emissions in 2020 were 31% greater than in 2015. Quanzhou is the city with the highest carbon emission in Fujian and is also one of the key cities for carbon peaking and the carbon neutrality of energy consumption. The manufacturing development outline 2025 of Quanzhou proposes the transformation and upgrading of 17 key industries. Since 2018, the growth of carbon emissions in Quanzhou has slowed. In recent years, Zhangzhou has accelerated its industrialization, as a result of which its carbon emissions in 2020 increased by 28% compared with 2015. Xiamen is one of the first low-carbon pilot cities in China, and the importance of Xiamen taking the lead in reaching the carbon peak is also emphasized in the energy savings and emission-reduction plan of Fujian Province. The carbon emissions in Xiamen in 2020 increased by 23% compared with 2015. After being accepted as a national low-carbon pilot city in 2017, Sanming's growth rate of carbon emissions decreased each year, so its carbon emissions in 2020 only increased by 6.6% compared with 2015. Longyan, Ningde, Putian, and Nanping all account for less than 10% of Fujian's carbon emissions, accounting for less than 10 million tons/year. The lowest emissions are in Nanping, accounting for about 3% of the province's energy-consumption-related carbon emissions from 2015 to 2020. See Figure 2.

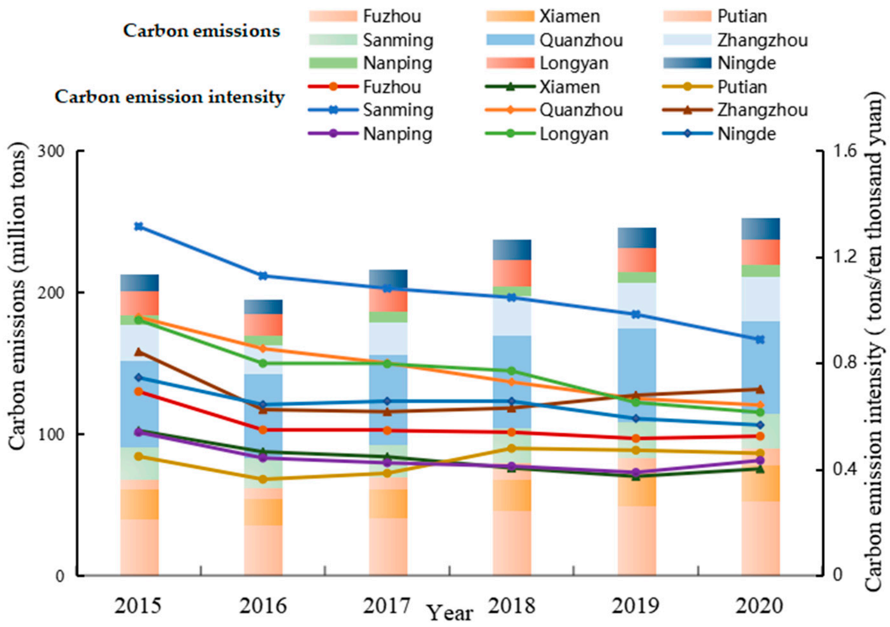

Figure 2. Carbon emissions and intensity in cities of Fujian Province.

2. Literature Review

"Carbon productivity" was first proposed by Kaya and Yokobori in 1993 at the Tokyo Conference on Global Environment, Energy, and Economic Development and is measured mainly by constructing an index to evaluate input and output [8]. Carbon emission efficiency reflects the balance between the economic benefits generated by labor, energy, technology, and other factors and the undesirable output carbon emissions [9]. Previous studies have shown that improving carbon emission efficiency is not only an important way to control energy inputs and achieve carbon reduction but is also a way to achieve ecologically sustainable development goals [10]. Depending on the factors involved in this evaluation, carbon emission efficiency can be divided into two types: single factor and total factor [11]. Single-factor carbon emission efficiency is usually expressed by the ratio between carbon emissions and factors such as carbon emission per capita [12] or carbon emission per unit GDP (i.e., carbon emission intensity) [13–15]. Total factor carbon emission efficiency is measured by using all input and output factors in methods such as stochastic frontier analysis (SFA) [4,16–18], data envelopment analysis (DEA) [5,9,18], and three-stage DEA with SFA [5,19–21]. For example, Zhao et al. constructed a three-stage DEA model that excludes the influence of the external environment and stochastic factors and reports that China's carbon emission efficiency is currently rising. They further specify that, although many regions have high technical efficiency, the overall efficiency is low due to the low scale efficiency [22]. Other research constructed an SBM model to measure the carbon emission efficiency in China and found that government participation correlates positively with carbon emission efficiency [23], whereas energy intensity and industrial structure correlate negatively with carbon emission efficiency [24]. Later, a total factor analysis combining DEA and the Malmquist index was developed to determine the temporal evolution of carbon emission efficiency [9,25–27]. In addition, the scholar applied a carbon emission Malmquist model and found that the eastern region of China has the highest carbon emission efficiency and production capacity and that technological progress drives improvements in carbon emission efficiency [28]. By constructing the decomposed Malmquist indexes of carbon emission efficiency, Fan found that technological progress, technical efficiency updates, openness to the outside world, government regulation, and improvement in the property rights structure all play a significant role in promoting carbon emission efficiency [29]. We found that many scholars have discussed the factors that influence carbon emission efficiency from different viewpoints; however, studies on city-level carbon emission efficiency remain insufficient.

To address this shortcoming, the present study builds a three-stage SBM-DEA model on the city scale and uses as input variables the number of industry employees, energy consumption, and land resources. The desirable output variables are the industrial added value above designated size (IAV) and GDP, and the undesirable output variable is carbon emissions. Then, we use the Malmquist index to quantify the energy-consumption-related carbon emission efficiency of Fujian Province and derive the potential carbon reduction of various cities in Fujian Province based on their carbon emission efficiency, which provides a decision-making basis for controlling energy inputs and achieving sustainable development. The main of the paper is to measure the carbon emission efficiency and carbon reduction potential of Fujian province at the city scale. The contributions of this paper are as follows. Firstly, the paper uses the emission factor method and the model provided in the Guide to Provincial Greenhouse Gas Inventories (Trial) to quantify the energy-consumption-related carbon emissions at the city scale. Secondly, three socio-economic and technological drivers were selected to explore the influence of carbon emission efficiency by means of SFA. Thirdly, the paper excluded the influence of external environmental factors and random factors on carbon emission efficiency and calculated the real carbon emission efficiency.

3. Materials and Methods

3.1. First Stage: Establishment of Undesirable Output SBM Model

The three-stage DEA model was initially developed by Freid [30]. In the model, a SFA is applied in the conventional DEA model to analyze environmental factors and random errors, and then the DEA model is used to evaluate the efficiency based on the adjusted input variables and raw output data. To quantify the energy-consumption-related carbon emission efficiency of Fujian Province from 2015 to 2020, this study constructed an input and output index system for the three-stage SBM-DEA model involving undesirable outputs based on the SBM model proposed by Tone [31] (see Table 1). The SBM is expressed as follows:

$$\rho = \min \frac{1 - \frac{1}{m}\sum_{i=1}^{m} \frac{S_{i0}^{-}}{x_{i0}}}{1 + \frac{1}{S_1+S_2}\left(\sum_{r=1}^{S_1} \frac{S_r^f}{y_{r0}^f} + \sum_{r=1}^{S_2} \frac{S_r^k}{y_{r0}^k}\right)} \tag{1}$$

$$\text{subject to} \begin{cases} S^- = x_0 - X\lambda \\ S^f = Y\lambda - y_0^f \\ S^k = y_0^k - Y\lambda, \end{cases} \tag{2}$$

$$S^-, S^f, S^k, \lambda \geq 0, \tag{3}$$

where $\rho \in [0,1]$ is the energy-consumption-related carbon emission efficiency of a city, x_0 and y_0 are the input and output, respectively, of the (decision-making units, DMU), with each DMU having S_1 desirable outputs and S_2 undesirable outputs. In Equation (2), S^- is the input redundancy, S^f is the shortage of a desirable output, S^k is the undesirable output, and λ is the weight of each DMU. If $\rho = 1$, and S^-, S^f, and $S^k = 0$, the DMU is not maximally efficient. If $\rho < 1$, the DMU efficiency decreases.

Table 1. SBM input and output index system.

Category	Index	Meaning	Symbol
Input indexes	Number of industry employees	Number of employees (10,000 persons)	P_1
	Energy resource	Fossil fuel consumption (10,000 tons standard coal)	P_2
		Energy consumption (100 million kW h)	P_3
Desirable output indexes	Land resource	Construction site area (km^2)	P_4
	Industrialization level	Above-size IAV (CNY 100 million)	O_1
	Economic development	GDP (CNY 100 million)	O_1
Undesirable output indexes	Carbon emission	Energy-consumption-related carbon emissions (10,000 tons)	U_1

3.2. Second Stage: SFA Regression Test

As described by Fried to avoid the influence of management factors [30], environment variables, and random error terms on the DMU carbon emission efficiency, SFA was used to quantify the influence of the three factors in the first stage. The SFA function is:

$$S_{ni} = f(Z_i\,;\ \beta_n) + v_{ni} + \mu_{ni}; i = 1, 2, \ldots, I; n = 1, 2, \ldots, N, \tag{4}$$

where S_{ni} is the slack of the input index n of city i, Z_i is the environment variable, β_n is the coefficient corresponding to environment variable i of the given city, v_{ni} and μ_{ni} are the mixed random error terms of the model, where μ reflects how the management factor affects the slack variable of the input index, v_{ni} reflects the random disturbance of the model, and $v \approx N(0, \sigma_V^2)$ [32]. Through SFA regression, all cities are adjusted to the same external environment

$$X_{ni}^A = X_{ni} + \left[max\left(f\left(Z_i; \hat{\beta}_n\right)\right) - f\left(Z_i; \hat{\beta}_n\right)\right] + [max(v_{ni}) - v_{ni}], n = 1, 2, \ldots, N, \tag{5}$$

where X_{ni}^A is the input after adjustment, X_{ni} is the input before adjustment, $\left[max\left(f\left(Z_i;\ \hat{\beta}_n\right)\right) - f\left(Z_i;\ \hat{\beta}_n\right)\right]$ is the adjustment of the external environment factor, and $[max(v_{ni}) - v_{ni}]$ is the adjustment of all cities to the same external environment.

3.3. Third Stage: Modification of SBM-DEA Model

After the adjustment by SFA regression, the original input X_{ni} is replaced with X_{ni}^A, and the output data are based on the original data. The SBM-DEA model is then used to quantify the efficiency. The obtained carbon emission efficiency does not take into account external environment factors and random error terms.

3.4. Malmquist Index

The Malmquist index (ML) was proposed by the economist Malmquist in 1953 and is widely used to calculate changes in productivity [33]. Considering that the energy-consumption-related carbon emission efficiency of Fujian Province varied over the years 2015–2020, it is unreasonable to simply compare the carbon emission efficiency between different years. Combining the ML index with the DEA model not only allows us to analyze the efficiency statically but also quantifies the change in carbon emission efficiency over time. The results indicate the total factor productivity (TFP) of different cities from year

t to year $t + 1$. If ML > 1, the carbon emission efficiency increases; if ML = 1, the carbon emission efficiency is constant; if ML < 1, the carbon emission efficiency decreases.

3.5. Potential in Carbon Reduction

The three-stage SBM-DEA model was used to quantify the target carbon emissions (*TCE*s) on the optimal production frontier for each city in each period, with actual carbon emissions (*ACE*s) as the reference. The undesirable output (carbon emissions) was converted by using the multiplicative reversal method, and the potential for city i to reduce carbon emissions ($CCRPi$) in the reporting period t is:

$$CCRP_{it} = (ACE - TCE)/TCE \tag{6}$$

3.6. Data Source

The data used in this study, such as the number of employees in an industry, energy consumption, land resources, above-scale IAV, GDP, the share of public budgets in GDP, the share of secondary industry, and financial investment in energy conservation and in environmental protection from 2015 to 2020, were obtained from the statistical yearbooks of Fujian Province and the various cities (2015–2020). To compensate for inflation, GDP was measured in 2015 currency.

4. Results

4.1. First Stage: Measurement of Carbon Emission Efficiency by SBM Model

We use SBMrun and the principle of constant returns to scale, meaning that the output is proportional to the input. Based on the existing research results [34–38], we construct the input–output index system, shown in Table 1, is used to quantify the carbon emission efficiency of different cities, and the results are shown in Figure 3.

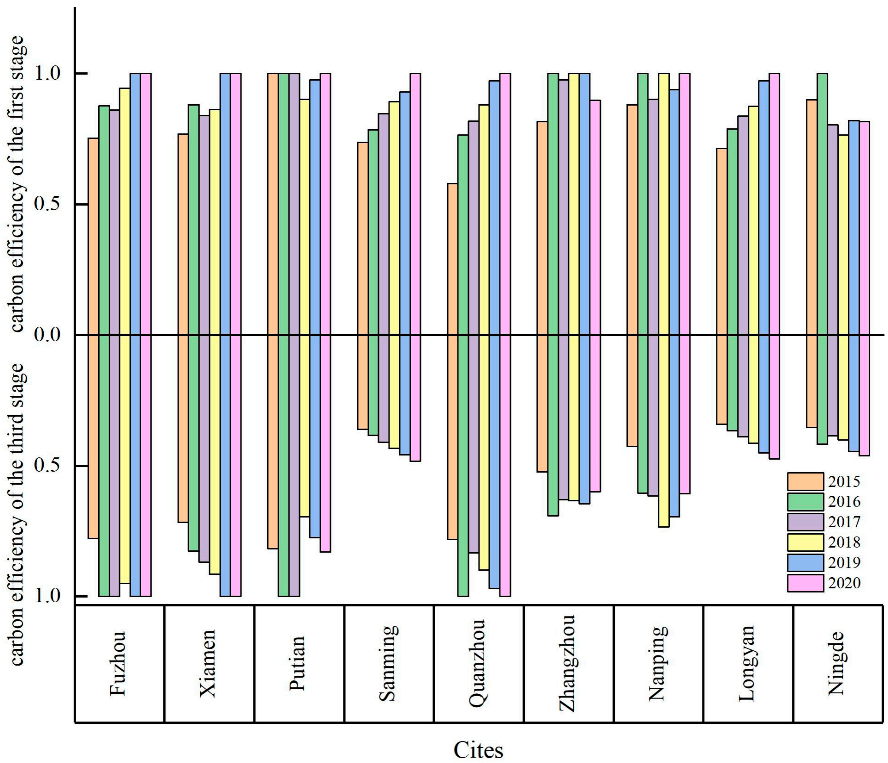

Figure 3. Carbon emission efficiency at the first and third stage in cities of Fujian Province from 2015 to 2020.

As shown in Figure 3, the carbon emission efficiency of Fuzhou, Xiamen, Putian, Quanzhou, and Zhangzhou averages over 0.9, and the carbon emission efficiency of the other cities averages between 0.8 and 0.9, suggesting that the overall carbon emission efficiency of Fujian Province is relatively high. This result is consistent with those of previous studies. Liu calculated the carbon emission efficiency of 30 provinces in mainland China and found that the average national carbon emission efficiency is only 0.513 [38], and regional variations in carbon emission efficiency are significant. Fujian Province is one of the benchmark provinces for economic greening and low-carbon transformation [39]. The carbon emission efficiency of most cities increased year-on-year from 2015 to 2020. That of Quanzhou increased the most, from 0.579 in 2015 to 1 in 2020, which is the efficiency frontier. The carbon emission efficiency of Ningde increased in 2016 and then decreased to fluctuate around 0.8, which is attributed to the excessive input of fossil energy, the number of employees in industry, and power consumption. The carbon emission efficiency of Putian is high, almost reaching the efficiency frontier, but the slack variables of fossil energy and construction site area existed only in 2018 and 2019. The year 2016 was the opening year of the 13th Five-Year Plan and the turning point of economic and social development in Fujian Province. In 2016, the carbon emission efficiency of all cities of Fujian Province increased rapidly, which is closely related to the development strategy of Fujian Province, notably the core improvement of ecological and environmental quality.

4.2. Second Stage: SFA Regression

Frontier 4.1 was used for SFA regression in the second stage. It used the slack values of the four variables measured in the first stage of SBM (i.e., number of employees in industry, fossil energy consumption, construction site area, and power consumption) as explained variables, and the three external management and environmental factors (i.e., contribution of the secondary industry to GDP growth and government investment in energy conservation and in environmental protection and share of expenditure in public budgets in GDP) as explanatory variables. The results appear in Table 2. The slack variables of fossil energy consumption, number of employees in industry, and power consumption all have $\gamma > 0.5$ and close to 1 to 1% significance, which is indicative of the inefficient management of the number of employees in industry, fossil energy consumption, and power consumption, so SFA regression is appropriate. The slack variables of construction site area have $\gamma < 0.5$, suggesting that the hypothesized environmental factors are not valid and that random error exerts a dominant influence. In Table 2, the LR (one-sided-error test) for the four input slack variables (i.e., number of employees in industry, fossil energy consumption, construction site area, and power consumption is 8.70, 4.76, 7.29, and 33.65, respectively, at 1% or 5% significance, suggesting that these four environment variables may significantly affect the carbon emission efficiency.

In terms of regression coefficients from Table 2, all four slack variables incur a negative share of expenditure in public budgets in GDP and pass the significance test at the 1% level, demonstrating that expenditure in public budgets correlates negatively with the slack variables. This result suggests that an increase in environmental factors could decrease redundancy (i.e., increase carbon emission efficiency). Thus, increasing the expenditure in public budgets could help reduce the input redundancy in energy consumption, the number of employees in industry, and the construction site area. Fossil energy consumption and power consumption correlate positively with secondary industry at 1% significance, indicating that an increase in secondary industry increases redundancy, thus decreasing carbon emission efficiency.

Table 2. Results of SFA regression in second stage.

Variable	Slack of Fossil Energy Consumption			Slack of Construction Site Area	
	Regression Coefficient	T-Value	Variable	Regression Coefficient	T-Value
β^0	22,377.65	3837.53	β^0	1573.45	421.83
Energy saving and environmental protection input	1211.33 ***	126.81	Energy saving and environmental protection input	108.92 ***	17.77
Contribution of the secondary industry to GDP growth	229.76 ***	5.89	Contribution of the secondary industry to GDP growth	−8.95	−0.71
Share of expenditure in public budgets in GDP	−15,089.96 ***	−1783.69	Share of expenditure in public budgets in GDP	−1140.17 ***	−239.58
σ^2	33,063.01 ***	28,707.10	σ^2	269.39 ***	54.95
γ	0.52 ***	5.75	γ	0.08	0.11
LR (test of one-sided error)	8.70 ***		LR (test of one-sided error)	4.76 ***	
Log likelihood	−344.60 ***		Log likelihood	−224.34	
Variable	**Slack of the Number of Industry Employees**			**Slack of Power Consumption**	
	Regression Coefficient	**T-Value**	**Variable**	**Regression Coefficient**	**T-Value**
β^0	5293.592	4.949	β^0	278,613.97	1042.07
Energy saving and environmental protection input	275.940 ***	4.180	Energy saving and environmental protection input	14,984.35 ***	172.29
Contribution of the secondary industry to GDP growth	−0.866	−0.047	Contribution of the secondary industry to GDP growth	231.79 ***	2.86
Share of expenditure in public budgets in GDP	−3454.491 ***	−4.575	Share of expenditure in public budgets in GDP	−185,211.57 ***	−495.85
σ^2	961.329 ***	1.789	σ^2	167,703.55 ***	122,367.56
γ	0.715 ***	4.056	γ	0.79 ***	17.64
LR (test of one-sided error)	7.29 ***		LR (test of one-sided error)	33.65 ***	
Log likelihood	−233.77 ***		Log likelihood	−371.61 ***	

Note: *** indicates significance at the 1% level.

4.3. Third Stage: SBM-DEA

Figure 4 shows carbon emission efficiency in the first and third stages. Putian, Xiamen, Sanming, Zhangzhou, Nanping, Longyan, and Ningde reduce their carbon emission efficiency, with Ningde, Longyan, and Sanming reducing it by 50% in the third stage, indicating an over-estimate of carbon emission efficiency for these cities in the first stage. This over-estimate of carbon emission efficiency in the first stage is attributed to the effective management of the external environment as the input of public budgets, which significantly affects carbon emission efficiency.

However, Fuzhou and Quanzhou increased their carbon emission efficiency, albeit to a lesser extent, indicating that the existing external environment hindered the improvement of carbon emission efficiency in the two cities. In particular, the slack variables of fossil energy consumption, number of industry employees, and power consumption have $\gamma > 0.5$ and to 1% significance, indicating the existence of ineffective environmental management. Fuzhou and Quanzhou ranked first and second, respectively, in the province in terms of carbon emissions over the past six years. Thus, in the future, carbon emission efficiency can be further increased by improving the management of fossil energy consumption, power consumption, and the number of industry employees.

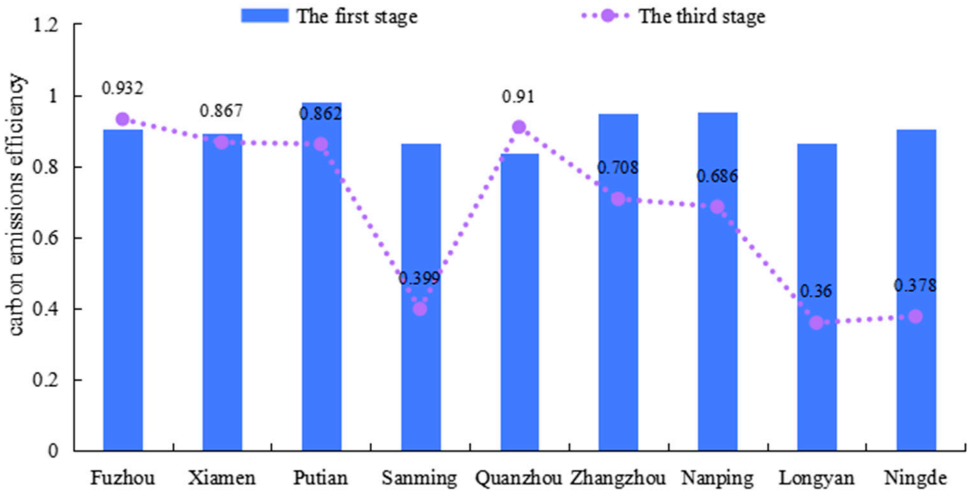

Figure 4. Carbon emission efficiency at the first and third stages in cities of Fujian Province.

Figure 3 shows the evolution over time of carbon emission efficiency of different cities in the third stage. From 2015 to 2020, the carbon emission efficiency of Fuzhou, Xiamen, and Quanzhou fluctuates and increases, reaching the efficiency frontier of one in 2020. The carbon emission efficiency of Putian reached one in 2016 and 2017, indicating that this city achieved the optimum state of carbon emission efficiency in these years. However, it then dropped to 0.695 as the lowest carbon emission efficiency in 2018 before rising again to 0.830 in 2020. The average carbon emission efficiency in Zhangzhou and Nanping from 2015 to 2020 was about 0.6, while the average carbon emission efficiency of Longyan, Sanming, and Ningde from 2015 to 2020 was about 0.4, indicating a poor state of carbon emissions. Compared with other cities with a high carbon emission efficiency, these four cities have a low carbon emission efficiency, which is attributed mainly to the small-scale efficiency. In other words, the input of these four cities was not proportional to their industrial scales compared with other cities with a high carbon emission efficiency, given that these four cities operate on a small industrial scale. For instance, the energy consumption of Zhangzhou and Sanming remained relatively constant from 2015 to 2020, but both the above-scale IAV and the carbon emission efficiency of Zhangzhou were about 50% greater than that of Sanming. From 2015 to 2020, the total accumulated energy consumption of Nanping was only 50% that of Ningde, but its cumulative IAV was 70% that of Ningde.

4.4. Causes of Carbon Emission Inefficiency

The redundancy of input variables and output variables in 2015 (see Table 3) is now used to further investigate the causes of carbon emission inefficiency. From 2015 to 2020, all nine cities in Fujian Province had redundant fossil energy and power consumption inputs and excessive undesirable output carbon emissions. Quanzhou has the highest fossil energy redundancy and excessive undesirable output carbon emissions. These results indicate that all cities have a large potential for carbon emission reduction by leveraging the inputs of energy structure, energy efficiency, and labor.

Table 3. Causes of energy-consumption-related carbon emission inefficiency in 2015.

City	Input Redundancy			Output Shortage			Excessive Undesirable Output
	Fossil Energy Consumption (10,000 Tons Standard Coal)	Construction Site Area	Number of Industry Employees (10,000 Persons)	Power Consumption	IAV	GDP	
Fuzhou	389.05	64.95	0.00	111.37	0.00	0.00	741.52
Xiamen	207.81	41.42	46.95	7.18	30.05	0.00	279.41
Putian	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Sanming	228.95	8.02	32.92	13.77	0.00	0.00	597.70
Quanzhou	678.04	11.21	145.51	6780.51	0.00	0.00	1525.92
Zhangzhou	323.00	3.40	26.71	2.99	0.00	13.47	630.84
Nanping	20.16	2.42	11.66	5.03	1.36	0.00	106.20
Longyan	159.74	4.73	52.35	13.77	23.96	0.00	406.46
Ningde	87.65	0.00	37.24	3.57	0.00	63.21	0.00

4.5. Dynamic Analysis of Carbon Emission Efficiency Based on the Malmquist Index

The ML indexes of carbon emission efficiency for the nine cities of Fujian Province from 2015 to 2020 were calculated by using the Dearun 3.0 Software, and the results appear in Figure 5. Herein, all the technical progress indexes are greater than 1, whereas TFP decreases. The technical progress index (Tech) and TFP undergo similar variations, demonstrating their positive correlation. The technical efficiency index Effch, scale efficiency index SE, and pure technical efficiency index PTE undergo similar variations and remain stable near one. The ML index fluctuates and decreases, as does the technical progress index, mainly as a result of a decrease in the latter, which reaches a minimum in 2016 and 2017.

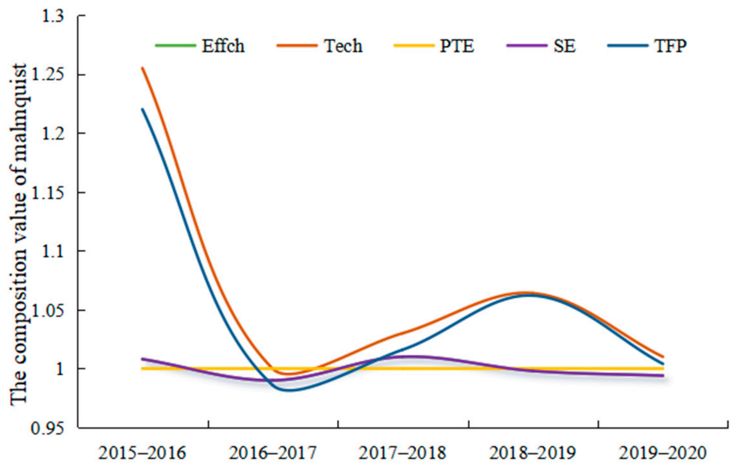

Figure 5. Decomposed Malmquist indexes of carbon emission efficiency in third stage. (Effch and SE overlap).

4.6. Potential for Improving Carbon Emission Efficiency

Improving the efficiency of carbon emission is of great significance to achieving the goal of "carbon peaking and carbon neutrality". Some scholars report that there is potential to improve the carbon emission efficiency of Chinese cities [38–40]. In particular, the countries along the "Belt and Road Initiative" have a low overall level of carbon emission efficiency, so the improvement in carbon emission efficiency in these developing countries will improve carbon emission efficiency along the Belt and Road Initiative [9]. According to the carbon emission efficiency measured by the three-stage SBM-DEA model, after the adjustment of the input–output indexes, the average carbon emission technical efficiency of Fujian Province in the third stage is 0.676, which is a 32.4% decrease with respect to the first stage and differs by 32.4% from the efficiency frontier. The scale efficiency in the third stage is 0.684, which is a 42.1% decrease with respect to the first stage and differs by 31.6% from the efficiency frontier. Thus, the carbon emission efficiency of Fujian Province has room for improvement.

The carbon emission scale efficiency and technical efficiency of cities other than Fuzhou and Quanzhou decreased significantly from 2015 to 2020. In the first stage, the carbon emission scale efficiencies for Sanming, Ningde, and Longyan were 0.878, 0.963, and 0.998, respectively, whereas the carbon emission scale efficiencies of these cities in the third stage decreased to 0.423, 0.413, and 0.424, respectively, far below the efficiency frontier, with the largest decrease exceeding 50%. Zhangzhou and Nanping decreased by 30%–50%, whereas Xiamen and Putian decreased by less than 15%. To summarize, the carbon emission efficiency of some cities depends strongly on the external environment and stochastic factors, and the external factors can reduce the carbon emission efficiency, which is mainly caused by a decrease in scale efficiency. Based on the results of existing studies, the carbon emission efficiency obtained by the three-stage SBM model is relatively accurate [39]. Some cities have good overall carbon emission efficiency, but the potential to improve the efficiency to the efficiency frontier differs between regions, as shown in Figure 6. Longyan, Ningde, and Sanming have a low carbon emission efficiency and a large potential of about 50% for improvement. In contrast, Fuzhou, Xiamen, and Quanzhou have a small potential of less than 10% for improving carbon emission efficiency, which indicates that the three cities already have good carbon emission efficiency.

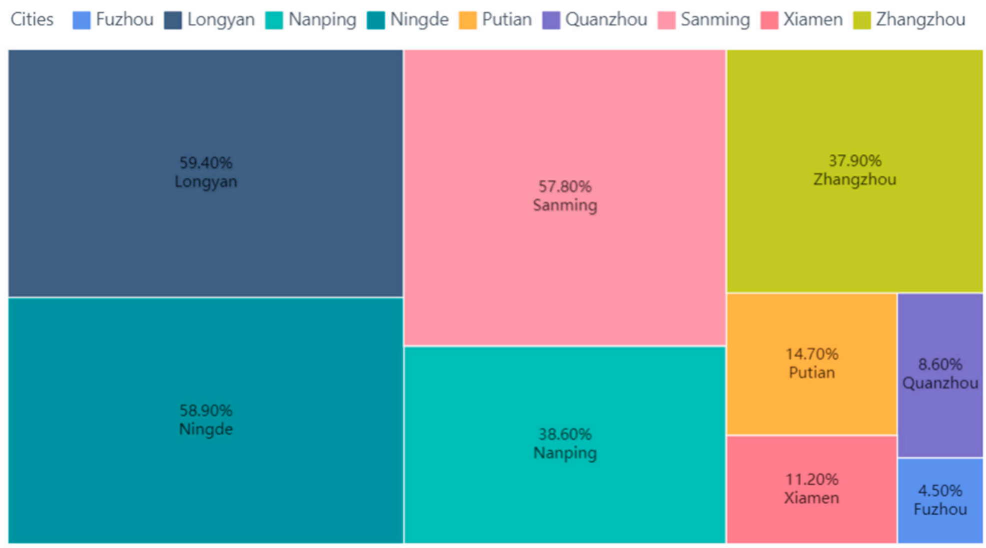

Figure 6. Potential of different cities to improve carbon emission efficiency.

4.7. Space for Carbon Emission Reduction of Different Cities

From the perspective of carbon emission efficiency, the potential of each city to reduce carbon emissions can be improved by exploring the degree to which each city has already optimized its carbon emission efficiency. The greater the ratio of available carbon emission reduction to *ACE*, the greater the potential for carbon emission reduction [40]. Thus, based on the targeted quantity of carbon emissions at the production–efficiency frontier and the *ACE*, the study obtained the potential for carbon emission reduction for the various cities and for the different years (see Figure 7). Figure 7 shows that the potential for carbon emission reduction for the various cities varies with time, depending on the existing carbon emissions. The potential for carbon emission reduction in Ningde increases, whereas that for all the other cities decreases to varying degrees, especially in Quanzhou, Fuzhou, and Xiamen, where the potential for carbon emission reduction decreases each year. Specifically, the carbon emission efficiency of Fuzhou, Quanzhou, and Xiamen in the third stage always exceeds 0.86, which is close to the efficiency frontier. In 2015, Sanming, Quanzhou, Longyan, and Zhangzhou had the maximum potential for carbon emission reduction, whereas Putian and Ningde had the smallest potential for carbon emission reduction. In 2020, Ningde's and Zhangzhou's possible carbon emission reduction was 6.02% and 9.50%, respectively, and that for all other cities was less than 1%. Therefore, of all the cities in Fujian Province, Zhangzhou and Ningde had the greatest potential for carbon emission reduction.

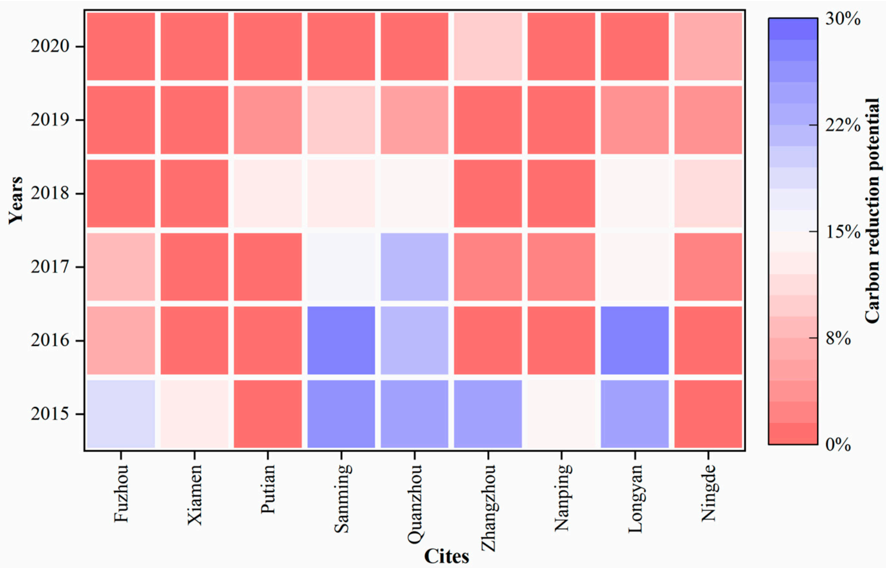

Figure 7. Possible carbon emission reduction for the cities of Fujian Province for 2015 to 2020.

5. Discussion

Increasing the contribution of the secondary industry to GDP growth will reduce carbon emission efficiency. Combined with the second stage SFA regression, the contribution of the secondary industry to GDP growth correlates positively with fossil energy consumption and power consumption and at 1% significance, indicating that increasing the contribution of the secondary industry to GDP increases the redundancy and thus reduces carbon emission efficiency. Since 2010, the contribution of the tertiary industry to GDP growth in Fujian Province increased year by year, while the proportion of the secondary industry remained stable and declined to 46.3% by 2020. As a result, the average carbon emission efficiency of these regions in Fujian Province was improved. This is consistent with the reports that the low carbon emission efficiency of some Chinese provinces is primarily due to the external environment. For example, some studies found that increasing the fraction of secondary industry increases carbon emissions, and increasing the fraction of the tertiary industry helps improve the efficiency of carbon emissions [19,41,42]. Adjusting the industrial structure is an important way to improve carbon emission efficiency [43].

On the contrary, increased public budgets helps to reduce the input redundancy of energy consumption, thereby increasing carbon emission efficiency. For the second-stage SFA regression, the quantity of secondary industry, of public budget in the GDP, and of government investment in energy conservation and environmental protection all serve as external environment variables. At 1% significance, the regression coefficients of all four slack variables show a negative correlation with expenditure in public budgets in GDP, indicating that public budgets correlate negatively with the slack variables, implying that increasing external environment factors would reduce redundancy and thus increase the carbon emission efficiency. This is consistent with reports that improving the government's environmental protection and environmental regulation improves China's carbon emission efficiency [44–46].

Figure 7 shows that Fujian Province still has carbon reduction potential in energy structure, energy efficiency, and labor input. However, the reduction potential of carbon emission efficiency in Fujian Province gradually weakened, mainly due to the decline in the technological progress index. Previous studies have also found that technological progress has a positive effect on improving the carbon emission efficiency index [47,48]. Similarly, the annual average of the Malmquist index undergoes the same variation as the technical progress index, and the decrease in the carbon emission efficiency is mainly due to the decrease in the technical progress index. Especially, Ningde, Nanping, and Longyan underwent the largest decrease in carbon emission efficiency, probably because these three cities did not improve their technology to keep pace with their expanded industrial scale in 2016 and 2017. This oversight lowered the technological efficiency, resulting in reduced carbon emission efficiency.

6. Conclusions and Suggestion

First, this study used the SBM-DEA to construct the system of input–output indicators to estimate and evaluate the carbon emission efficiency at the city scale in Fujian Province from 2015 to 2020, and then used the Malmquist index to quantify the changes in the carbon emission efficiency. Finally, we quantify the potential for carbon emission reduction based on the carbon emission efficiency and the "distance" to the production frontier, which can provide ideas for future carbon emission reduction.

The overall carbon emission efficiency of energy consumption in Fujian increased from 2015 to 2020, but the degree of improvement gradually weakening, owing primarily to the decline of the technological progress index. Increasing the contribution of the secondary industry to GDP growth will reduce carbon emission efficiency. While an increase in public budgets helps reduce the input redundancy of energy consumption, it also helps to increase the carbon emission efficiency. As a result, we suggest that upgrading the industrial structure helps reduce carbon emissions, particularly in cities with a majority of a secondary industry, such as Quanzhou City in Fujian Province, which suggests that the transformation and upgrading of the industrial infrastructure should be accelerated to improve carbon efficiency.

In terms of the annual average potential improvement in the carbon emission efficiency in each city, Longyan, Ningde, and Sanming are the regions with a low carbon emission efficiency, with a large improvement potential in carbon emission efficiency of about 50%. Fuzhou, Xiamen, and Quanzhou have effective carbon emission efficiency, with less than a 10% improvement potential. In 2020, Ningde's and Zhangzhou's potential for carbon emission reduction was 6.02% and 9.50%, respectively, and the potential for carbon emission reduction for all other cities was less than 1%. Therefore, in the future industrialization process of Fujian Province, it is recommended to reasonably control the growth of coal consumption in different regions and cities, and accelerate the construction of a clean, low-carbon, safe, and efficient energy supply system with the multi-wheel drive coal, oil, gas, nuclear and renewable energy, and coordinated development. In particular, green and low-carbon development in the industrial sector, energy saving and carbon reduction transformation in the steel industry, and strict control of new capacity in the non-ferrous metal industry.

To summarize, in Fujian Province's future industrialization, cities and regions should improve the technical level and rationally control the growth of coal consumption and accelerate the development of a clean, low-carbon, safe, and efficient energy supply system driven by a variety of energy sources, such as renewable energy, nuclear, and low-carbon emission coal, oil, and gas sources. In addition, coordinated development should be promoted. The iron and steel industry should receive particular attention for green and low-carbon development, and the non-ferrous-metal industry should be strictly regulated to ensure new production capacity.

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