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Impact of Financial Inclusion on the Efficiency of Carbon Emissions: Evidence from 30 Provinces in China

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Abstract: Carbon emissions have become a serious environmental problem worldwide, with the greenhouse effect and global temperature increase being the main areas of concern. Financial inclusion is a means to increase the welfare of citizens and promote sustainable development. Development of financial inclusion may have a big impact on carbon emissions. This study uses data from 2011 to 2019 to do panel Tobit regression and check the effect of financial inclusion on the efficiency of carbon emissions, which is calculated by the super-efficiency Slacks-Based Measure (SBM) -data envelopment analysis (DEA) method. The results show that financial inclusion decreases the efficiency of carbon emissions. Moreover, financial inclusion could reduce the efficiency of carbon emissions by increasing the proportion of tertiary industries. Moreover, the effect varies in each region. Thus, following these conclusions, we propose several related policy implications. The government should strengthen the supervision of money due to financial inclusion and ensure that the investment should be put into environmental projects. In addition, it needs to pay attention to carbon emissions generated in the process of industrial upgrading. More access to renewable energy is an effective measure to solve the problem of higher carbon dioxide emissions.

Keywords: financial inclusion; carbon emissions; panel Tobit regression; super-efficiency SBM-DEA

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1. Introduction

Carbon emissions have become one of the most significant and serious environmental problems at present, and are the main cause of the greenhouse effect [1–3]. The release of carbon dioxide (CO_2) causes serious environmental damage and has negative economic and social effects [4–7]; this phenomenon has attracted the attention of many economists and environmentalists. The 101st Federal Climate Policy, set by the U.S. federal government, aims to reduce emissions. Furthermore, it also proposes to reduce the increasing global temperature (Δtemperature) by mitigating gases. Moreover, in 2016, the Paris Agreement, signed by 196 countries, took effect, aiming to limit global warming. In China, economic growth promotes carbon reduction in the long run [8,9]; however, currently, overuse of energy resources worsens the quality of the environment by emitting carbon dioxide [10]. In China, the government has set a goal to reach a carbon emission peak before 2030, as well as accomplish carbon neutrality by 2060. To achieve this goal, it is possible to accelerate renewable energy transition to support sustainable economic growth and introduce green projects to the finance sector [11].

Carbon emissions are associated with economy, industrial structures, environmental regulations, government interventions, and so on. Among these factors, financial development is crucial in the process of carbon emissions. Currently, traditional financial institutions have obvious drawbacks, such as high loan costs, complex procedures, and strict requirements for companies. Thus, traditional finance has developed into financial inclusion. In fact, financial inclusion implies that customers including individuals, companies, or other groups may enjoy the convenience of financial services easily for their aims. In addition, financial services are delivered without harming environment [12–14]. Financial inclusion is beneficial in reducing poverty, promoting economic growth, and ensuring educational equity [15–18]. The Development Plan for China's Financial Inclusion 2016–2020 was put forward in 2016, which aims to allocate finance resources to financial inclusion and strengthen the supervision to guarantee the safety of financial inclusion. Moreover, this policy tends to make inclusive finance better serve sustainable development. Therefore, in response to the environmental problem of carbon dioxide emissions, it is valuable to determine the exact effect of financial inclusion on carbon reduction and the mechanism.

This study concentrates on the impact of financial inclusion on the efficiency of carbon emissions by finding out the critical factors of carbon emissions. Section 2 provides a brief summary of the related research. Section 3 clarifies the methodology and data. Section 4 discusses the experimental outcomes, and Section 5 presents the conclusions and essential policies.

2. Literature Review

2.1. Development of Finance and Its Effect on Carbon Emissions

Many studies have been carried out regarding the relationship between financial development and carbon emissions. The relationship can be described in two parts, namely, positive and negative. On the one hand, Boutabba [19] studied the Indian economy to do an empirical study and argued that financial development indeed promotes carbon emissions. Jiang and Ma [20] also reached the same conclusion for China. However, Charfeddine and Kahia [21] insisted that financial development and emissions of carbon dioxide have a weak relationship. On the other hand, Claessens and Feijen [22] pointed out that financial development reduces transaction costs. It tends to alleviate the issue of information asymmetry. Due to low transaction costs, loans can increase, which can be used for investment in environmentally friendly projects to improve environmental quality. Tamazian et al. [23] further studied carbon emissions and financial development. They found that for some countries, financial development is beneficial in reducing carbon emissions. Tamazian and Rao [24], Shahbaz et al. [25], and Salahuddin et al. [26] also found that financial development can significantly reduce CO_2 emissions. Even the United Nations encourages climate finance to mitigate carbon emissions because large investments may reduce emissions in line with the Paris Agreement. Briefly, current studies find that financial development may have beneficial or harmful impacts on carbon emissions under different circumstance.

2.2. The Relationship between Financial Inclusion and Emissions of Carbon Dioxide

Further study explored the relationship between financial inclusion and emissions of CO_2 because financial inclusion is the latest achievement as finance expands. Furthermore, the effect can be split into two aspects, namely, reducing and increasing carbon emissions.

Financial inclusion enables people to have quicker and easier access to goods and services, thereby promoting green finance and large investments in sustainable projects. Moreover, financial inclusion provides green and renewable energy companies with more efficient financing to further improve their green technology and conduct better environmental governance. It also creates precise opportunities for traditional companies and industries to transform, rather than continue, their operations that tend to produce large amounts of pollution. Qin et al. [27] found that financial inclusion is actively connected to carbon emission reduction. Shahbaz et al. [28] also supported this opinion through their empirical study.

However, financial inclusion may have another effect on carbon emissions. When individuals or companies engaged in manufacturing and industries have limited financial aid, large amounts of pollution such as gas and industrial waste is produced. Moreover, customers tend to buy money- and energy-intensive electronic equipment such as refrigerators, air conditioners, and high-fuel vehicles with the help of financial inclusion. To begin with, Alam et al. [29] emphasized that financial development could hinder carbon productivity. Dong et al. [30] found that financial inclusion significantly increases carbon emissions and aggravates the greenhouse effect.

Additionally, Mehmood [31] used an autoregressive distributed lag model to deal with the cross-section data and concluded that financial inclusion exacerbates emissions of carbon dioxide, together with globalization and economic growth; the exception being renewable energy. Le et al. [32] and Haider et al. [33] reached similar conclusions. However, Renzhi et al. [34] argued that the association of the two parts is nonlinear, which is an inverted shape [35]. It follows the environmental Kuznets curve (EKC).

Therefore, similar to the relationship of financial development and carbon emissions, financial inclusion can have impeccable or adverse impacts on emissions of carbon dioxide. Most of the researchers prefer to study the relationship between financial development or financial inclusion and the total amount of carbon emissions. Few papers conduct investigation between financial inclusion and the efficiency of carbon emissions.

2.3. Measurement of the Efficiency of Carbon Emissions

In order to explore the intrinsic influence of financial inclusion on carbon emissions, we use the efficiency of carbon emissions instead of the amount of carbon dioxide to evaluate the performance of carbon emission. A related study showed that the measurement of efficiency of carbon emissions can be classified into two parts: single and total factors. Initially, scholars use single factors such as CO_2 emissions per capita, CO_2 intensity per capita, and carbon productivity to evaluate the performance of emissions of CO_2 [36–43]. However, single factors only consider the outputs of carbon emissions; they ignore the inputs such as energy, carbon-containing resources, labor, capital, and R&D. Considering the inputs and outputs of carbon emissions, we use data envelopment analysis (DEA) to assess the performance of carbon emissions. Zhou et al. [44] applied a Malmquist CO_2 emission performance index to achieve the total factor CO_2 emissions performance, using CO_2 as undesirable output. Wang et al. [45] promoted a new CO_2 emissions performance index by adopting a stochastic frontier analysis.

In line with the above, most of the scholars use the DEA model to figure out the performance of carbon emissions and take the results as the efficiency of emissions of CO_2.

2.4. Contributions of This Paper

The contributions of our research lie at three aspects: Firstly, this paper establishes the framework to explore the relationship of financial inclusion and efficiency of carbon emissions, rather than the absolute amount of carbon emissions studied by a lot of researchers, which concentrates more on efficiency level. Secondly, we use the super-efficiency SBM-DEA method to calculate efficiency of carbon emissions when considering carbon dioxide as an undesirable output and decompose financial inclusion and efficiency of carbon emissions into three dimensions, respectively. This latest approach to calculating efficiency overcomes the shortcomings of traditional calculation methods and DEA measures. Moreover, this decomposition makes the research on the impact of financial inclusion on efficiency of carbon emissions more detailed and in-depth. Thirdly, the results of this study give new direction to policy makers at the level of increasing efficiency of carbon emissions. According to the various efficiency of each province, local government authorities are capable of putting forward differentiated policies.

3. Methodology and Data

3.1. Panel Tobit Regression

Considering the previous research and the current data, the panel Tobit regression model is the most suitable in estimating the influences of financial inclusion on the efficiency of emissions of CO_2. The data of efficiency of emissions of CO_2 belong to censored data—the value of which are between 0 and 2. Hence, the panel Tobit regression model [46–53] is suitable in reducing the aggregate bias. The related econometric model is as follows:

$$TE_{i,t} = \beta_0 + \beta_1 LnIFI_{i,t} + \beta_2 \mathbf{X_{i,t}} + \varepsilon_{i,t} \tag{1}$$

where i,t denote the province and year, respectively. $TE_{i,t}$ denotes the efficiency of carbon emissions of province i in year t. $LnIFI_{i,t}$ denotes the degree of financial inclusion of province i in year t. $X_{i,t}$ represents a vector of the control variables, including regional gross domestic product (GDP) per capita (LnGDP_per), the degree of innovation (Patent_per), the level of employment (Employment), the structure of property (Property), the structure of energy (Energystr), the degree of government contribution (Gov), and the degree of R&D (Inno). $\varepsilon_{i,t}$ is the error term. The specific variables are provided in Table 1.

Table 1. Definition of variables.

Classification	Name of Variables	Symbols	Definition
Explanatory variable	Financial inclusion	LnIFI	Logarithm of the index of financial inclusion
Explained variable	Efficiency of carbon emission	TE	Technical efficiency calculated by the super-efficiency SBM-DEA model
Mediator variable	Third industry	Third_industry	The ratio of regional output value of third industry to its GDP
Control variables	Regional GDP per capita	LnGDP_per	Logarithm of each province's GDP per capita
	The degree of innovation	Patent_per	Quantity of patent per capita
	The level of employment	Employment	The ratio of urban private and individual employees to the total number of employees
	The structure of property	Property	The ratio of the number of employees in state-owned units to that of employees at the end of the year
	The structure of energy	Energystr	The ratio of coal consumption to total energy consumption
	The degree of government contribution	Gov	The ratio of government fiscal expenditure to GDP
	The degree of R&D	Inno	The ratio of R&D expenditure to fiscal expenditure

3.2. Mediation Effect Model

Apart from the direct influence of financial inclusion on the efficiency of emissions of carbon dioxide, this study also explores the indirect effect by other channels. Because industrial production is part of the region gross product, industrial structure is one of the most significant causes in the process of carbon production and carbon emissions. The amount of CO_2 can make a big difference because of various industrial structures. Thus, industrial structure can be considered as the mediator in the process of financial inclusion affecting efficiency of carbon emissions. With this, we decided to use the stepwise regression in constructing the mediation effect model. The related mediation effect model is as follows:

$$Third\_industry_{i,t} = \beta_0 + \beta_1 LnIFI_{i,t} + \beta_2 \mathbf{X_{i,t}} + \varepsilon_{i,t} \tag{2}$$

$$TE_{i,t} = \beta_0 + \beta_1 InIFI_{i,t} + \theta Third\_industry_{i,t} + \beta_2 \mathbf{X_{i,t}} + \varepsilon_{i,t} \tag{3}$$

where $Third\_industry_{i,t}$ is the ratio of regional output value of third industry to GDP. In the mediation model, the first step regressed the mediator variable $Third\_industry_{i,t}$ and the explanatory variable $LnIFI_{i,t}$. The second step is to regress the explained variable $TE_{i,t}$, which is calculated by super-efficiency SBM-DEA model and the explanatory variable $LnIFI_{i,t}$, together with a mediator variable $Third\_industry_{i,t}$.

3.3. Super-Efficiency SBM-DEA

According to the literature review of the measurement of efficiency of carbon emissions, it is obvious that the DEA method has become the mainstream method of assessing efficiency of carbon emissions. This method takes various outputs and inputs into consideration and calculates efficiency on the increasing or decreasing return of scale condition. Thus, this study adopts the DEA approach to obtain technical efficiency to assess the performance on the efficiency of emissions of CO_2. Originally, DEA consists of two models: CCR and BCC [54–60]. The first one was proposed by Charnes, Cooper, and Rhodes [54], while the second one was presented by Banker et al. [57] based on the CCR model. The basic assumption is that the return to scale is constant; however, it can increase or decrease. Thus, the BCC model is more suitable in calculating the efficiency of the variable industries. However, traditional DEA models (CCR and BCC) depend on radial and angular methods. There is an obvious problem that the two models are unable to consider the slack variable. Moreover, the score of each decision-making unit (DMUs) is only between 0 and 1. If the scores of many DMUs are 1, it will be difficult to rank their efficiency. The undesirable outputs such as CO_2 or other pollution can also be produced with desirable outputs such as GDP. Traditional DEA models cannot deal with the problem of undesired outputs. Tone [61] proposed a slacks-based measure (SBM) model to compensate the drawbacks of traditional DEA, and settle the trouble of slack inputs or outputs. In addition, when Seiford and Zhu [62] suggested a super-efficiency model, Tone [63] proposed the imperfect super-efficiency SBM-DEA model. Then, Cooper et al. [64] proposed a SBM model that took the undesirable outputs into consideration. Finally, we decided to choose the super-efficiency SBM model with the undesirable output emission of CO_2 on the assumption of VRS. We propose the model as follows.

We assumed that each DMU has m inputs, r_1 desirable outputs, and r_2 undesirable outputs, and the number of DMUs is n. Inputs, desirable outputs, and undesirable outputs can be represented by the three vectors, respectively: $x \in R^m, y^g \in R^{r_1}, y^b \in R^{r_2}. X = [x_1, x_2, x_3 \ldots x_N] \in R^{N\times M}, Y^g = \left[y_1^g, y_2^g, y_3^g \ldots y_N^g\right] \in R^{N\times r_1}$, $Y^b = \left[y_1^b, y_2^b, y_3^b \ldots y_N^b\right] \in R^{N\times r_2}$ are matrices of the three variables.

$$P_{SE-SBM} = \min \frac{1 - \sum_{i=1}^{m} \frac{\overline{x}_i}{x_{ik}}}{1 + \frac{1}{r_1 + r_2}\left(\sum_{i=1}^{r_1} \frac{\overline{y}_i^g}{y_{ik}^g} + \sum_{i=1}^{r_2} \frac{\overline{y}_i^b}{y_{ik}^b}\right)}$$

$$\text{s.t.} \begin{cases} \overline{x} \geq \sum_{j=1,\neq 0}^{N} \lambda_j x_i \\ \overline{y}^g \leq \sum_{j=1,\neq 0}^{N} \lambda_j \, y_i^g \\ \overline{y}^b \geq \sum_{j=1,\neq 0}^{N} \lambda_j \, \overline{y}_i^b \\ \overline{x} \geq x_k,\ \overline{y}_i^g \leq y_k^g,\ \overline{y}_i^b \geq y_k^b \\ \overline{y}_i^g \geq 0,\ \overline{y}_i^b \geq 0, \lambda \geq 0 \end{cases} \tag{4}$$

where λ represents the combination proportion of decision-making units. The efficiency of emissions of CO_2 can be greater than 1. The higher the score each DMU gets, the better the level of efficiency.

3.4. Selection of Indicators for Carbon Emissions

Following the research on the efficiency and using the super-efficiency SBM-DEA model, the indices used in this study include four inputs, one desirable output, and one undesirable output. The inputs variables are labor, capital, R&D expenditure, and consumption of energy. The desired output is measured as the regional GDP of each province, and the undesirable output is represented by the emissions of CO_2. Table 2 shows the specific input–output data.

Table 2. Input and output variables.

Types	Variables	Explanation
Inputs indices	Labor	Measured by the quantity of employees in the whole three industries.
	Capital	Currently, data of capital of each province cannot be obtained directly. Most of the researchers use the perpetual inventory method to calculate the total capital of each province. Researchers take different years as the time of base capital stock and assume different depreciation rates. In this study, we assume that the depreciation rate is 9.6% and divide the gross fixed capital formation in 2000 by 10% as the base period capital stock of the province. However, due to few unavailable data that are not published by the National Bureau of Statistics, an interpolation method is used to estimate the nominal gross fixed capital formation. Finally, we calculate the capital of each province using the perpetual inventory method.
	R&D expenditure	Measured by the expenditure in the aspect of R&D.
	Consumption of energy	The ratio of urban population to total population.
Desirable output	Regional GDP	Measured by the GDP of each province.
Undesirable output	Amount of CO_2	Measured by emission of CO_2 of each province.

3.5. Data Source

Because of the missing values from Tibet, we use the data of 30 provinces (according to the geographic location and the level of economic development in China, the 30 provinces can be divided into three regions: eastern regions, central regions, and western regions. Eastern regions include the following provinces: Beijing, Shanghai, Tianjin, Shandong, Guangdong, Jiangsu, Hebei, Zhejiang, Hainan, Fujian, and Liaoning. Central regions include the following: Jilin, Heilongjiang, Hunan, Anhui, Shanxi, Jiangxi, Henan, and Hubei) in China from 2011 to 2019. Most of these data originate from the CSMAR Database and Wind database. In addition, the data from the Financial Inclusion Index are obtained from the "Digital Financial Inclusion Index" compiled by the Digital Finance Research Center of Peking University. The data of carbon emissions are from the Carbon Emission Accounts and Datasets (CEADs). Other data come from the "Chinese Statistical Yearbook" and the provincial statistical yearbooks.

4. Empirical Results

4.1. Descriptive Statistics

As shown in Tables 3 and 4, the technical efficiency average of carbon emissions is slightly low, which means that there is a high possibility that a few provinces can improve their efficiency using various methods. However, there are also some cities with a high efficiency, including Beijing, Guangdong, and Jiangsu, whose efficiency is higher than 1. Even the efficiency of Shanghai is 0.97, which is close to 1; Beijing, Guangdong, Jiangsu, and Shanghai are the most developed provinces in China with good economic growth. This shows that more developed provinces have a better ability in dealing with carbon emissions; thus, they have a higher efficiency. Regarding financial inclusion, the average value is 5.151. However, the standard deviation is higher than the other variables, except for Patent_per, which implies that the level of financial inclusion varies widely across regions. Furthermore, the minimum and maximum values of Third_industry are 0.3 and 0.84, respectively, indicating that at least 30% and at most 84% of GDP is contributed by the third industry.

Table 3. Descriptive statistics.

Variable	Obs	Mean	Std. Dev.	Min	Max
TE	270	0.52	0.325	0.135	1.68
LnIFI	270	5.151	0.67	2.909	6.017
Third_industry	270	0.465	0.097	0.3	0.84
LnGDP_per	270	10.812	0.434	9.706	12.009
Patent per	270	14.001	20.397	0.132	121.183
Employment	270	0.224	0.118	0.065	0.655
Property	270	0.089	0.032	0.039	0.202
Energystr	270	0.394	0.148	0.012	0.687
Gov	270	0.249	0.103	0.11	0.628
Inno	270	0.053	0.131	0	1.145

Table 4. Technical efficiency of 30 provinces.

	2011	2012	2013	2014	2015	2016	2017	2018	2019	Average
Anhui	0.43	0.41	0.42	0.38	0.41	0.35	0.34	0.37	0.42	0.39
Beijing	1.26	1.24	1.29	1.26	1.26	1.30	1.39	1.33	1.34	1.30
Chongqing	0.39	0.38	0.41	0.39	0.42	0.41	0.40	0.37	0.48	0.41
Fujian	0.53	0.69	1.05	0.50	0.42	1.07	0.61	0.45	0.59	0.66
Gansu	0.34	0.30	0.34	0.41	0.32	0.29	0.20	0.21	0.25	0.29
Guangdong	1.09	1.11	1.02	1.02	1.01	1.03	1.01	1.07	1.23	1.07
Guangxi	0.44	0.36	0.46	0.40	0.29	0.44	0.40	0.39	0.33	0.39
Guizhou	0.44	0.40	0.34	0.26	0.27	0.31	0.29	0.32	0.28	0.32
Hainan	0.40	0.39	0.36	0.36	0.33	0.33	0.32	0.30	0.29	0.34
Hebei	0.39	0.59	1.28	0.39	0.30	0.44	0.30	0.25	0.26	0.47
Heilongjiang	0.51	0.48	0.36	0.40	0.33	0.30	0.24	0.17	0.20	0.33
Henan	0.44	0.40	0.42	0.29	0.52	1.22	0.37	0.34	0.43	0.49
Hubei	0.61	0.48	0.60	1.36	1.24	0.69	0.36	0.41	0.47	0.69
Hunan	0.68	0.59	0.57	0.58	0.51	0.44	0.36	0.34	0.44	0.50
Inner Mongolia	0.57	0.48	0.34	0.29	0.27	0.32	0.23	0.24	0.20	0.33
Jiangsu	1.15	0.79	1.15	1.17	0.61	1.23	1.65	1.68	0.73	1.13
Jiangxi	1.31	1.22	0.75	0.40	0.38	0.48	0.43	0.45	0.43	0.65
Jilin	0.54	0.43	0.48	0.71	1.02	0.50	0.28	0.19	0.22	0.48
Liaoning	0.53	0.50	0.50	0.35	0.53	1.03	0.30	0.24	0.27	0.47
Ningxia	0.24	0.23	0.21	0.20	0.18	0.18	0.17	0.15	0.16	0.19
Qinghai	0.29	0.26	0.22	0.21	0.19	0.17	0.16	0.13	0.15	0.20
Shaanxi	0.45	0.40	0.38	0.33	0.39	0.55	0.33	0.30	0.35	0.39
Shandong	0.76	0.72	0.47	0.38	0.38	0.51	0.43	0.40	0.32	0.48
Shanghai	1.15	1.17	1.03	0.60	0.58	1.01	1.00	1.02	1.18	0.97
Shanxi	1.12	1.17	0.36	0.23	0.23	0.25	0.26	0.27	0.24	0.46
Sichuan	0.43	0.55	0.72	0.41	0.37	0.59	0.48	0.40	0.49	0.49
Tianjin	0.59	0.53	0.58	0.52	0.55	0.48	0.45	0.27	0.30	0.47
Xinjiang	0.35	0.29	0.32	0.27	0.21	0.24	0.23	0.24	0.20	0.26
Yunnan	0.38	0.35	0.26	0.24	0.24	0.28	0.23	0.28	0.28	0.28
Zhejiang	0.69	0.70	0.70	0.75	0.78	0.73	0.67	0.69	0.55	0.70

4.2. Correlation of Variables

In this study, it is imperative to apply a correlation test between the variables, except for the explained variables. It is clear that all the variables, including the control variables, have weak correlations between them. Because there is no absolute value of correlation more than 0.8, there is no multicollinearity problem. Similarly, the variance inflation factor (VIF) method also can be adopted to determine whether there is a multicollinearity problem. Following the results of the VIF, it is obvious that all the VIF values are less than 4, which implies that all the variables are independent. Table 5 presents the correlations and VIF data.

Table 5. Matrix of correlations.

Variables	LnIFI	Third_Industry	LnGDP_Per	Patent Per	Employment	Property	Energystr	Inno
LnIFI	1.000							
Third_industry	0.535	1.000						
LnGDP_per	0.162	0.043	1.000					
Patent_per	0.347	0.390	−0.012	1.000				
Employment	−0.148	0.255	0.018	0.019	1.000			
Property	−0.344	−0.583	−0.089	−0.347	−0.112	1.000		
Energystr	0.120	0.159	0.063	−0.208	0.395	0.100	1.000	
Inno	−0.052	−0.029	0.157	−0.097	0.135	0.183	0.497	1.000

Variables	VIF
LnGDP_ per	2.290
Third_industry	2.110
LnIFI	2.070
Gov	1.900
Energystr	1.850
Employment	1.780
Property	1.550
Inno	1.450
Patent_per	1.090
Mean	1.790

4.3. Panel Tobit Regression Results

As shown in Table 6, we found the coefficient of LnIFI to be significantly negative at the 1% level, regardless of the number of control variables, which indicates that the expansion of financial inclusion reduces the efficiency of emissions of CO_2. Moreover, only the two control variables—LnGDP_per and Gov—pass the significance test, whereas the coefficients of the other control variables are not significant, indicating that these variables do not really have influences on the efficiency of carbon emissions.

Table 6. Regression results.

Variables	TE							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
LnIFI	−0.080 ***	−0.162 ***	−0.149 ***	−0.148 ***	−0.132 ***	−0.130 ***	−0.123 ***	−0.123 ***
	(−4.65)	(−6.02)	(−5.39)	(−5.33)	(−4.32)	(−4.25)	(−4.07)	(−4.09)
LnGDP_per		0.329 ***	0.327 ***	0.331 ***	0.309 ***	0.359 ***	0.396 ***	0.397 ***
		(4.03)	(4.05)	(3.96)	(3.68)	(3.91)	(4.35)	(4.37)
Patent_per			−0.002 *	−0.002 *	−0.002 *	−0.002	−0.002	−0.002
			(−1.76)	(−1.74)	(−1.66)	(−1.63)	(−1.32)	(−1.33)
Employment				−0.037	−0.022	0.019	−0.048	−0.054
				(−0.21)	(−0.12)	(0.10)	(−0.26)	(−0.29)
Property					1.265	1.183	1.452	1.463
					(1.34)	(1.24)	(1.56)	(1.57)
Energystr						0.329	0.352	0.357
						(1.31)	(1.46)	(1.48)
Gov							−0.635 **	−0.610 *
							(−2.00)	(−1.90)
Inno								−0.060
								(−0.52)
Constant	0.930 ***	−2.203 ***	−2.214 ***	−2.260 ***	−2.226 ***	−2.899 ***	−3.205 ***	−3.218 ***
	(9.14)	(−2.82)	(−2.86)	(−2.81)	(−2.82)	(−3.09)	(−3.47)	(−3.48)
Observations	270	270	270	270	270	270	270	270
Number of provinces	30	30	30	30	30	30	30	30

*t-statisticsl in parentheses *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.*

4.4. Mediation Effect Results

We applied three regression models to establish the mediation model in order to investigate the indirect impact of financial inclusion on emissions of CO_2. As shown in Table 7, the overall efficiency of carbon emissions decreases as the financial inclusion increases. Because of the significantly positive coefficient of LnIFI, financial inclusion has good influence on the advance of the third or tertiary industry. China is currently upgrading their industrial structure to transform the primary and secondary industries into tertiary industry. However, the coefficient of Third_industry is −0.716, which is significantly negative at the 5% level. This means that the spread of financial inclusion can diminish the capacity of carbon emissions by increasing the proportion of the tertiary industries in production.

Table 7. Mediation effect.

	(1)	**(2)**	**(3)**
Variables	**TE**	**Third_industry**	**TE**
LnIFI	−0.123 ***	0.010 **	−0.104 ***
	(−4.09)	(2.09)	(−3.34)
Third_industry			−0.716 **
			(−2.02)
LnGDP_per	0.397 ***	0.108 ***	0.427 ***
	(4.37)	(6.28)	(4.58)
Patent_per	−0.002	0.001 ***	−0.001
	(−1.33)	(3.62)	(−0.96)
Employment	−0.054	0.075 **	0.061
	(−0.29)	(2.46)	(0.32)
Property	1.463	−0.425 **	1.219
	(1.57)	(−2.19)	(1.25)
Energystr	0.357	−0.152 ***	0.268
	(1.48)	(−3.13)	(1.05)
Gov	−0.610 *	0.313 ***	−0.469
	(−1.90)	(4.19)	(−1.36)
Inno	−0.060	0.036 **	−0.036
	(−0.52)	(2.07)	(−0.32)
Constant	−3.218 ***	−0.769 ***	−3.317 ***
	(−3.48)	(−4.24)	(−3.52)
Observations	270	270	270
Number of provinces	30	30	30

*t-statisticsl in parentheses *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.*

4.5. Robustness Check

To avoid the contingency of the experiment, an alternative model can be used to conduct a robustness check. Because of the limitation of data uniqueness, alternative explanatory variables or the explained variable method cannot be used for the robustness check. Thus, we select a fixed-effect model instead of a panel Tobit regression model. We also deleted the Patent_per variable from the control variables to explore robustness. As shown in Table 8, the results are the same as before, even though the values of the coefficients changed, and all the coefficients are significant.

Table 8. Robustness check: fixed effect model.

	(1)	**(2)**	**(3)**
Variables	**TE**	**Third_industry**	**TE**
LnIFI	−0.094 ***	0.011 **	−0.077 **
	(−2.84)	(2.22)	(−2.36)
Third_industry			−1.514 ***
			(−3.63)

Table 8. *Cont.*

	(1)	(2)	(3)
Variables	**TE**	**Third_industry**	**TE**
LnGDP_per	0.266 **	0.115 ***	0.439 ***
	(2.21)	(6.24)	(3.47)
Employment	0.036	0.083 ***	0.162
	(0.18)	(2.65)	(0.80)
Property	0.909	−0.465 **	0.206
	(0.63)	(−2.12)	(0.15)
Energystr	0.762 **	−0.126 **	0.571
	(2.17)	(−2.34)	(1.65)
Gov	−0.523	0.470 ***	0.188
	(−0.97)	(5.67)	(0.33)
Inno	−0.028	0.034 *	0.023
	(−0.24)	(1.88)	(0.20)
Constant	−2.125 *	−0.879 ***	−3.456 ***
	(−1.68)	(−4.53)	(−2.68)
Observations	270	270	270
Number of provinces	30	30	30

*t-statisticsl in parentheses *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.*

4.6. Heterogeneity

4.6.1. Geographical Heterogeneity

As shown in Table 9, the coefficients of LnIFI based on three regions are all negative, but the coefficient of LnIFI in the eastern provinces is not significant. This means that the impact of financial inclusion on the capacity of emissions of CO_2 is significant in the central and western regions. Furthermore, it seems that the impact is strongest in the central regions. One possible reason is that the central regions have the highest potential and fastest development speed, and financial inclusion has the biggest effect on the efficiency during the development period. In addition, according to the EKC, the central and western regions are at a stage where economic development is harmful to the environment.

Table 9. Geographical heterogeneity.

	(1)	(2)	(3)
Variables	**Eastern**	**Central**	**Western**
LnIFI	−0.092	−0.195 ***	−0.056 ***
	(−1.26)	(−2.70)	(−3.81)
LnGDP_per	0.506 **	0.290	0.138 **
	(2.54)	(1.52)	(2.32)
Patent_per	−0.002	0.003	−0.002
	(−0.91)	(1.01)	(−1.41)
Employment	−0.490	1.843 **	−0.044
	(−1.46)	(2.47)	(−0.44)
Property	0.946	−1.229	0.670
	(0.59)	(−0.89)	(0.90)
Energystr	0.138	1.202 **	0.215
	(0.35)	(2.44)	(1.17)
Gov	−1.373 *	−2.219 **	−0.260
	(−1.74)	(−2.52)	(−1.57)
Inno	−0.136	0.168	0.003
	(−0.66)	(0.14)	(0.06)
Constant	−4.056 **	−1.968	−0.905
	(−2.10)	(−1.02)	(−1.41)
Observations	99	72	99
Number of provinces	11	8	11

*t-statisticsl in parentheses *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.*

4.6.2. Decomposition of Technical Efficiency

Technical efficiency can be divided into pure technical efficiency (PTE) and scale effect (SE). PTE is the production efficiency of an enterprise or a region because of various factors such as management and technology. If PTE = 1, then it indicates that the use of all inputs is efficient at the current technology level. SE is the production efficiency because of firm size. SE reflects the distance between the actual scale and the optimal operation scale. From Table 10, negative coefficients suggest that financial inclusion has an adverse impact on not only technical efficiency, but also PTE and SE.

Table 10. Decomposition of technical efficiency.

	(1)	**(2)**	**(3)**
Variables	**TE**	**PTE**	**SE**
LnIFI	−0.123 ***	−0.094 *	−0.066 ***
	(−4.09)	(−1.79)	(−2.90)
LnGDP_per	0.397 ***	0.146	0.246 ***
	(4.37)	(0.97)	(3.28)
Patent_per	−0.002	0.002	−0.002 *
	(−1.33)	(0.83)	(−1.74)
Employment	−0.054	−0.010	−0.225
	(−0.29)	(−0.03)	(−1.59)
Property	1.463	1.851	−0.248
	(1.57)	(1.18)	(−0.31)
Energystr	0.357	−0.307	0.195
	(1.48)	(−0.65)	(0.92)
Gov	−0.610 *	−0.774	0.001
	(−1.90)	(−1.43)	(0.00)
Inno	−0.060	0.118	−0.110
	(−0.52)	(0.58)	(−1.30)
Constant	−3.218 ***	−0.175	−1.569 **
	(−3.48)	(−0.11)	(−2.02)
Observations	270	270	270
Number of provinces	30	30	30

*t-statisticsl in parentheses *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.*

4.6.3. Decomposition of Financial Inclusion

Financial inclusion can be grouped into coverage breadth, depth of use, and degree of digitalization. The data of coverage breadth, depth of use, and degree of digitalization are all from the "Digital Financial Inclusion Index." To avoid multicollinearity, we also take the logarithm of these three variables. Coverage breadth reflects the coverage of financial services in each province. The depth of use measures the abundance of financial services and the actual total user because it involves payment services, such as money fund, credit, insurance, investment, and so on. Degree of digitalization reflects the occupation of digitization of financial services. Digitization is convenient and less costly. As shown in Table 11, coverage breadth, depth of use, and degree of digitalization all diminish the efficiency of CO_2 emissions.

Table 11. Decomposition of financial inclusion.

	(1)	**(2)**	**(3)**	**(4)**
VARIABLES		**TE**		
LnIFI	−0.123 ***			
	(−4.09)			
LnUsage_depth		−0.099 ***		
		(−3.27)		
LnCoverage_breadth			−0.096 ***	
			(−4.14)	

Table 11. *Cont.*

	(1)	(2)	(3)	(4)
VARIABLES		**TE**		
LnDigital_level				−0.068 ***
				(−2.70)
LnGDP_per	0.397 ***	0.340 ***	0.394 ***	0.295 ***
	(4.37)	(3.71)	(4.35)	(3.36)
Patent_per	−0.002	−0.002	−0.002	−0.002 *
	(−1.33)	(−1.39)	(−1.51)	(−1.74)
Employment	−0.054	−0.092	−0.069	−0.069
	(−0.29)	(−0.50)	(−0.38)	(−0.37)
Property	1.463	1.945 **	1.719 *	1.938 **
	(1.57)	(2.08)	(1.89)	(2.03)
Energystr	0.357	0.360	0.392	0.388
	(1.48)	(1.45)	(1.61)	(1.57)
Gov	−0.610 *	−0.687 **	−0.626 *	−0.682 **
	(−1.90)	(−2.08)	(−1.95)	(−2.09)
Inno	−0.060	−0.035	−0.082	−0.065
	(−0.52)	(−0.31)	(−0.72)	(−0.56)
Constant	−3.218 ***	−2.739 ***	−3.366 ***	−2.403 ***
	(−3.48)	(−2.92)	(−3.57)	(−2.63)
Observations	270	270	270	270
Number of provinces	30	30	30	30

*t-statisticsl in parentheses *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.*

5. Conclusions and Policy Implications

5.1. Conclusions

This study used the 2011–2019 panel data of 30 provinces in China to test the relationship between financial inclusion and the efficiency of carbon emissions. To begin with, this study introduced a panel Tobit regression model, the super-efficiency SBM-DEA method, and mediation effect. Then, it presented the result of descriptive statistics and concrete data of the efficiency of carbon emissions, where the overall efficiency is not high except for four megacities. Briefly, there is a high possibility that the efficiency of emissions of CO_2 is correlated with the degree of development in the provinces. Moreover, the results of the panel Tobit regression model suggest that financial inclusion has a serious influence on the capacity of CO_2 emissions. The results of the mediation effect show that the spread of financial inclusion can decrease the efficiency of carbon emissions by increasing the proportion of tertiary industry, and financial inclusion promotes the development of tertiary industry. This is because financial inclusion enables the tertiary industry to have easier and quicker access to financing. Companies tend to do business transformation starting from primary industry to tertiary industry. A large amount of CO_2 is produced in the food, accommodation, transportation, and other services; thus, financial inclusion finally reduces the efficiency of carbon emissions. In addition, the robustness check was carried out using a fixed effect model, which guarantees the reliability of the empirical results. We can obtain the same conclusion from a fixed-effect model. Finally, following the results of heterogeneity, financial inclusion has more significant effects on the efficiency of carbon emission in central and western regions in China. No matter the sub-indicator of financial inclusion or efficiency of carbon emissions, the conclusion remains the same.

5.2. Policy Implications

According to the aforementioned conclusions, several related policy implications can be developed. First, the negative relationship between financial inclusion and the efficiency of emissions of CO_2 indicates that major steps are required to achieve the goals of carbon peak and carbon neutrality in terms of the policies and regulations of the Chinese government concerning financial inclusion. The government needs to strengthen the supervision of financial inclusion, particularly in relation to high energy-consuming companies and energy-intensive industries. It is important to check the pollution that these companies produce, as well as the emissions such as wastewater and gas, to determine whether the pollution exceeds the standards and the emissions exceed the related standards. Moreover, renewable energy is a suitable approach to curb carbon emissions [65–69]. Government agencies should focus on green projects related to renewable energy in the finance sector and assess the quality of green projects. Money should be allocated to the most environmental projects rather than inefficiently sustainable ones. Second, the mediation effect proves that financial inclusion promotes the development of tertiary industry, but its development reduces the efficiency of carbon emissions. The tendency of the increasing proportion of tertiary industry cannot be impeded. Individuals or companies that engage in food services, accommodation, trade, and transportation within the tertiary industry enable environmental friendliness during production and operations. The government could make restrictions regarding the number of high energy consumption companies and strengthen the support for renewable companies in tertiary industry, which would promote the upgrade of sustainable and environmental industry.

Third, the results of heterogeneity indicate that even though the coefficient of the eastern regions is not significant, financial inclusion reduces the efficiency in the eastern, central, and western regions. Due to the different development level of each province, related policies will vary. In terms of provinces in the eastern region, they tend to have high efficiency of carbon emissions, which means they have a high ability to deal with the problem of carbon emissions. The excess financial resources could be distributed to those provinces with low efficiency. For these provinces, local government needs to advocate for renewable energy and green companies. Moreover, companies need to put the capital obtained from financial inclusion into the process of R&D, especially the study of green technology, to achieve the goal of production with zero emissions. In the future, financial inclusion could enable those provinces with low efficiency to own more high-tech environmental companies, and China could realize carbon neutrality.

In summary, efficiency is a critical indicator evaluating the performance of carbon reduction. Moreover, the DEA method is a frontier approach measuring efficiency based on the latest literature. However, this paper has some limitations. Firstly, the super-efficiency SBM DEA method can be replaced with the super-efficiency SBM-Malmquist DEA method, as well as the SFA method. The panel Tobit regression model also can be replaced by the spatial panel Tobit model. Finally, there are other possible mediator variables.

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