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Estimation and Analysis of Carbon Emission Efficiency in Chinese Industry and Its Influencing Factors—Evidence from the Micro Level

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Abstract: A major goal of the "14th Five-Year Plan" phase is to promote the green transformation of industrial enterprises to address the 'dual carbon' challenge. Utilizing the China Industrial Enterprises Database and the Polluting Enterprises Database, this paper calculates the carbon emissions of Chinese industrial enterprises from 2001 to 2010 at the micro level. It presents an analysis of the heterogeneity of carbon emission efficiency (TPI) in industrial enterprises, as well as the factors influencing corporate TPI. This study finds that enterprises within a subdivided industry exhibit heterogeneous levels of TPI, with carbon emissions largely affected by the structure of energy consumption. The researchers suggest accelerating the transition of industrial enterprises to green technology and argue that carbon emission policies should shift from controlling direct total targets to strengthening market-oriented policy tools. Carbon reduction targets should be more stringent for enterprises with lower TPI, considering the heterogeneity among enterprises. To meet the challenges of emission reduction, industrial enterprises are encouraged to actively reform their energy consumption structure. Government policies should aim to reduce clean energy costs and encourage the use of clean energy by industrial enterprises.

Keywords: industrial enterprises; carbon emission efficiency; heterogeneity; carbon emission policy

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1. Introduction

The Intergovernmental Panel on Climate Change (IPCC) has reported in its Fifth Assessment Report that global ocean and land temperatures have increased by 0.85 °C from the end of the 19th century to the beginning of the 21st century, and this trend is on the rise. Between 2000 and 2012, the average global ocean and land temperature was 0.78 °C higher than during the period of 1850–1900. Climate warming has brought significant impacts to human society, including increasingly frequent natural disasters, rising sea levels, and the melting of perennial snow mountains, continuously eroding the foundations of human existence. The mainstream view, supported by the IPCC's Fifth Assessment Report, holds that global warming is caused by human activities [1]. However, some scholars, like Singer [2], hold different opinions. They argue that, considering the Earth's evolutionary cycle, it cannot be proven that global warming is solely caused by human activities, and suggest that solar activity is a main reason for the Earth's climate warming. Despite the lack of conclusive evidence directly linking greenhouse gas emissions to global warming, objective data support that human activities have significantly contributed to carbon emissions that have led to global warming. In order to slow down climate change, reducing carbon emissions is vital. Several climate change agreements have been formed in recent years: the Kyoto Protocol in 2005, the Bali Roadmap for emissions reductions in 2007, the Copenhagen Agreement in 2009, and the Paris Agreement in 2015, all committed to global cooperation to slow the trend in climate warming. China, currently the world's largest emitter of carbon dioxide, accounting for 28% of global emissions in 2015, has committed to reducing its carbon emission intensity by 40–45% by 2020 and 60–65% by 2030 compared to the 2005 levels, and to peak its absolute emissions by 2030 or even earlier. As an energy-intensive industry, industrial energy consumption and carbon dioxide emissions account for about 70% of the national total, making the industry significantly important for China to achieve its emission reduction targets.

Existing research on carbon emissions primarily focuses on the regional level, with limited attention paid to the enterprise level. In reality, carbon emissions efficiency varies greatly among enterprises. For instance, carbon emissions at the enterprise level have been calculated by Xu et al. [3], indicating that the key to achieving coordinated emission reductions lies in reducing the source of emissions. Increasing energy efficiency is more effective than reducing output to reduce enterprises' sources of pollution. However, the scope of this study was limited to calculations and did not explore the underlying factors that determine enterprise carbon emission reductions. In addition to calculating enterprise carbon emissions, Wang et al. [4] analyzed a sample of Chinese industrial enterprises but did not conduct further analysis. They found that the average energy intensity of major industrial products, both domestically and internationally, is at or even higher than the world's advanced level when compared to the product energy intensity of super-large companies and key energy-consuming firms in China. However, the average energy-saving level of the industry lags behind. It is evident that enterprises within the same industry in China emit significantly different levels of carbon dioxide [5].

The purpose of this paper is to examine the influencing factors and potential heterogeneity of carbon emission efficiency (TPI) as addressed in the existing literature, utilizing the Industrial Enterprises Database and the Pollution Emission Database. The TPIs of enterprises within subdivided industries show significant differences, with no trend towards narrowing these gaps. These findings contribute to understanding the paradox of China experiencing "micro-level technological catch-up" while overall carbon emission reduction efficiency lags behind. Based on this discovery, there is a need for China to further focus its capacity on more efficient enterprises to enhance its TPI in the future. Additionally, this paper delves into the factors influencing the energy efficiency of enterprises, investigating the determinants of TPI among enterprises within the same industry using a matched sample of Chinese polluting enterprises and industrial enterprises from 2001 to 2010. Heterogeneity tests will be conducted based on industry, region, years of operation, and industry agglomeration. The findings suggest that an enterprise's scale significantly explains its TPI, indicating that further improvements in TPI are likely to be influenced by this factor.

This paper offers the following innovations and contributions: Unlike the existing literature that focuses on regional and listed company carbon emissions, this study introduces novelty in two key aspects. First, it leverages microdata from Chinese enterprises to calculate carbon emission efficiency and explores the heterogeneity of efficiency among these enterprises. Second, it goes beyond merely measuring carbon emissions by studying the factors affecting the carbon emission efficiency of industrial enterprises and the characteristics of the heterogeneity of carbon emission efficiency at the Chinese enterprise level. It also investigates which factors have the most significant impact on the efficiency of enterprise carbon emissions. These efforts enrich the understanding of carbon emission efficiency characteristics in Chinese enterprises.

The remainder of the paper is structured as follows: The second part discusses the factors that drive carbon emissions and their efficiency. The third part details the data sources and processing methods for each variable, including the method for calculating the TPI. The fourth part identifies the factors influencing the efficiency of enterprises in terms of carbon emissions and conducts heterogeneity analyses of enterprise TPI from the perspective of enterprise heterogeneity, providing a basis for the policy analysis presented in the subsequent sections. Conclusions and policy recommendations are presented in the final part of the paper.

2. Literature Review

Carbon emissions productivity is defined by Jiang et al. [6], who propose the ratio of carbon emissions to GDP as a measure of it, suggesting that as human production activities expand, carbon emissions will increase, adversely affecting human production and life. A carbon emission productivity measure was also developed by Sun [7]. Carbon emissions have been measured as a percentage of the added value of industrial activities over a period of time by Mielnik and Goldemberg [8]. Ang [9] considered energy intensity as an indicator of a country's TPI. Hampf and Rødseth [10] used industrial investment as a measure of TPI. Based on a comprehensive review of existing research, Zhang et al. [11] have proposed comparing various TPI indicators, including per capita carbon emissions and GDP per capita carbon emissions. It is evident that the majority of the scholars mentioned above have studied the efficiency of carbon emissions from the perspective of a single factor. However, carbon emissions are not merely a function of one factor but also of the structure of the economy, the industry, the energy system, and technological advancement. Zhou et al. [12], who measured TPI by incorporating industrial structure, energy structure, and technological progress, have therefore begun to take a multi-factor approach to the measurement of carbon emissions.

The SBM-DEA model is used to analyze the effects of energy structure on the economy and carbon emissions, drawing on sample data from 29 countries or regions. Lin et al. [13] have utilized sample data from 29 countries or regions worldwide for their analysis using this model. Kuang et al. [14] have applied the SBM-DEA model to estimate land use efficiency in China, using provincial samples. Zhou et al. [15] have calculated China's construction industry's TPI using the SBM-DEA model and examined the influencing factors through the GVAR model. Zaim and Taskin [16] have suggested that the SFA model could calculate a TPI index based on data from OECD countries. Zofio and Prieto [17] have calculated TPI based on data from the European Union. Ramanathan [18,19] has explored the efficiency of carbon emissions under total factor conditions, evaluating the relationship between carbon emissions, energy consumption, economic development, and other factors. Zhou et al. [20], using carbon emission data from 20 countries worldwide, calculated TPI using the Malmquist index method and studied its dynamic changes and influencing factors using the nonparametric Bootstrap method. Using carbon emission data from 44 countries between 2000 and 2009, Talukdar and Meisner [21] have calculated TPI and analyzed how changes in industrial structure have affected TPI from the perspectives of agriculture, industry, and services.

Kortelainen [22] has analyzed the influencing factors of TPI using dynamic panel data regression and utilized carbon emission data from the EU from 1990 to 2003 to calculate TPI for 20 EU countries. Techniques such as CCR, BCC, three-stage DEA, and the Malmquist index have been widely employed to calculate TPI amid the continuous development of computer technology [23]. Ramanathan [24] has conducted a comparison of the CCR and BCC models using inputs and outputs of greenhouse gas emissions for 17 African countries. Yao et al. [25], analyzing carbon emissions for 30 provinces in China for 2011, calculated energy efficiency, TPI, and carbon reduction potential of those provinces and suggested countermeasures for reducing carbon emissions. The DEA model and fuzzy clustering algorithms were combined by Xia et al. [26] based on emissions data from China's industrial sector from 2002–2007 to estimate the efficiency of various industries' carbon emissions. A study by Zhou et al. [27], using carbon emission data from 50 countries to calculate TPI and predict the carbon emissions of these countries, employed the MCPI index method for calculating TPI. Based on data on carbon emissions in 76 countries worldwide, Maradan and Vassiliev [28] have estimated the marginal abatement cost of carbon emissions for these countries using the nonparametric directional distance function in the DEA model. A comparative study of SFA and DEA models, based on US carbon emission data, was conducted by Reinhard et al. [29]. To calculate the TPI of the industrial sector, Tone et al. [30] have used data from the UK industrial sector. The DEA model was utilized by Hailu [31] to estimate the marginal abatement cost of Canada's papermaking sector based on Canadian carbon emission data.

There has been considerable study on TPI from both regional and industry perspectives, as evidenced by the aforementioned literature. However, with enterprises being the main entities responsible for carbon emissions, few scholars have focused on calculating and analyzing the factors affecting their TPI. This paper aims to calculate the carbon emissions of industrial enterprises and analyze the factors affecting their TPI using the China Industrial Enterprises Database and the Enterprise Pollution Emission Database.

3. Calculation of Enterprise Carbon Emission Efficiency

3.1. Data Sources and Processing

This paper compares enterprise-level TPI differences and analyzes the factors influencing them using data from China's Polluting Enterprises (2001–2010) and China Industrial Enterprises (2001–2009), matching these datasets. According to the China Polluting Enterprises data, 85% of China's major pollutants originate from enterprises that produce industrial output, consume energy, and emit pollution. The monitoring system included 219,810 industrial enterprises between 2001 and 2010. Environmental protection departments compile these data based on self-reporting by polluting enterprises, with local environmental protection departments conducting irregular inspections at the county level to ensure data accuracy. These environmental microeconomic data are regarded as the most comprehensive and reliable in China [32]. Since 2006, pollution emissions from the thermal power industry have been excluded from environmental monitoring statistics due to changes in the environmental statistics reporting system during the "11th Five-Year Plan" period. To ensure data consistency and continuity, all sample firms in the fields of electricity, heat production, and supply were excluded from the analysis. Additionally, following the sequential matching method proposed by Brand et al. [33], and drawing upon the practices of Cai and Liu [34] and Feenstra et al. [35], value-added data and financial information for the sample enterprises were obtained. The first step involves processing the industrial and pollution discharge databases according to Brandt [33]. The second step matches the data according to the enterprise name and year with the pollution discharge database. The third step uses the organization code and year for matching. The fourth step merges the matched data from the second and third steps, removing duplicates. Finally, the industrial enterprise database after matching is obtained. For industrial output, enterprise sales, and fixed assets, extreme values within the top and bottom 5% quantiles were excluded from the analysis. Overall, the sample matched 58% of enterprises with industrial outputs greater than 10 million yuan, achieving a matching rate of 69% for enterprises with higher outputs.

3.2. Calculation of Carbon Emission Efficiency

By comparing carbon emissions to enterprise income, this paper measures the TPI of enterprises following the approach of Lyubich et al. [36], which also makes this indicator comparable with other efficiency measurement indicators. Specifically, this is detailed in Formula (1).

$$TPI = \frac{\text{Output}}{\text{Cabon}} \tag{1}$$

Coal, coke, fuel oil, diesel, and natural gas are included in the China Polluting Enterprises database to account for enterprise carbon emissions. For this paper, the IPCC's carbon emission coefficients were utilized to calculate the carbon emissions from different energy sources.

3.3. Calculation Results of Carbon Emission Efficienc Heterogeneity

This study examined the carbon emissions efficiency of different enterprises within subdivided industries, drawing on the approaches of Syverson [37] and Hsieh and Klenow [38].

As a first step, the enterprises were subdivided into 320 subsectors based on the four-digit codes of the national economy, of which 104 were classified as high-energy consumption industries. This classification provided a reference for measuring the degree of difference in other variables among firms within subdivided industries. Following this, we obtained the distribution function of the natural logarithm of the efficiency of reducing carbon emissions of companies within each subdivided industry. To quantify the heterogeneity of TPI within each subdivided industry, the differences between the 90th and 10th percentiles, the 75th and 25th percentiles, as well as the standard deviation within each subdivided industry, were calculated. The 320 subdivided industries exhibited considerable heterogeneity in the efficiency of carbon emissions. For example, when using the same amount of energy, a company at the 90th percentile of the industry TPI distribution can increase its industrial output by 53.9 times compared to a company at the 10th percentile (see Figure 1a).

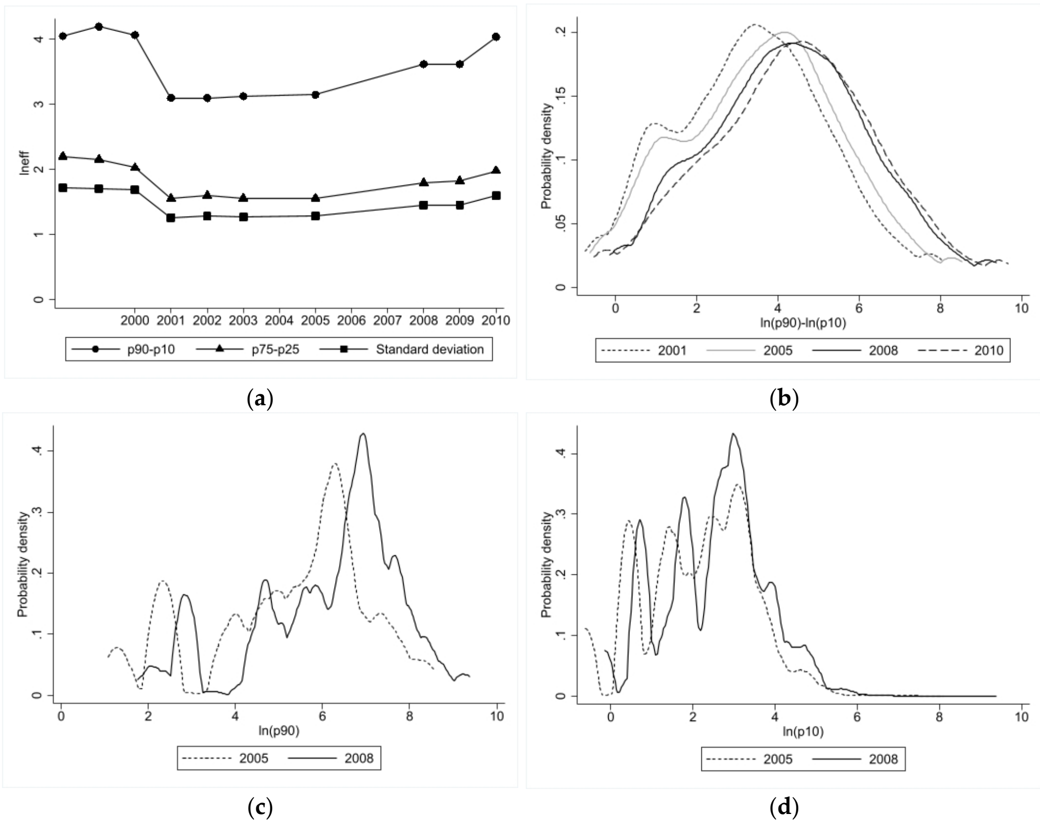

Figure 1. Results of TPI heterogeneity calculation. (**a**) Time Trend of TPI; (**b**) Kernel Density of TPI; (**c**) Changes in TPI of High-Efficiency Enterprises; (**d**) Changes in TPI of Low-Efficiency Enterprises.

In addition, there has been no decrease in the significant disparity in carbon emissions among enterprises within the same industry in China over time, as illustrated in Figure 1a. TPI distributions within subdivided industries consistently show a difference of 7.39 times between enterprises at the 90th percentile and those at the 10th percentile with the same energy input. According to Figure 1b, since 2005, there has been a slight increase in the heterogeneity of TPI across industries in China. The implementation of the 'Top 1000 Energy-Consuming Enterprises Program' by the Chinese government in 2006 as part of the 11th Five-Year Plan may explain this change. This program required the largest thousand enterprises in nine key energy-consuming industries to save 100 million tons of coal and established legal documents to set binding energy-saving targets for enterprises. As shown in Figure 1c, the energy efficiency distribution of high-efficiency industrial enterprises in China (at the 90th percentile of energy productivity distribution within subdivided industries) shifted noticeably to the right in 2006, resulting in further improvements in energy efficiency. On one hand, these large, high-efficiency enterprises implemented advanced technology and equipment to achieve energy-saving goals. On the other hand, enterprises struggling to meet energy-saving tasks were forced to reduce production, transferring demand to other enterprises in the market, thereby increasing market demand, raising related industrial product prices, and leading to lower industry entry barriers and an influx of low-productivity enterprises. Figure 1d shows how the TPI distribution in low-efficiency industrial enterprises in China shifted from the right to the left between 2006 and 2007. Consequently, the increased carbon emissions efficiency of high-efficiency enterprises and the inflow of low-efficiency enterprises into the market have contributed to an increase in the disparity in carbon emissions efficiency within the industry.

Considering that the steel, coal, petrochemical, building materials, chemical, and papermaking industries are generally regarded as high-energy-consuming industries, this paper further analyzes these key subdivided industries. As depicted in Figure 2, the coal mining and washing industry exhibits the greatest heterogeneity in TPI. With the same energy input, the output of enterprises at the 90th percentile of energy productivity distribution within this industry is 396 times that of enterprises at the 10th percentile. This indicates that the coal mining and washing industry contains a significant number of backward capacities relying on resource-consuming expansion, urgently requiring the shutdown of low-efficiency enterprises and the elimination of outdated capacities. Although the heterogeneity of TPI in the steel industry has gradually decreased since 2004, there has been a rising trend in recent years.

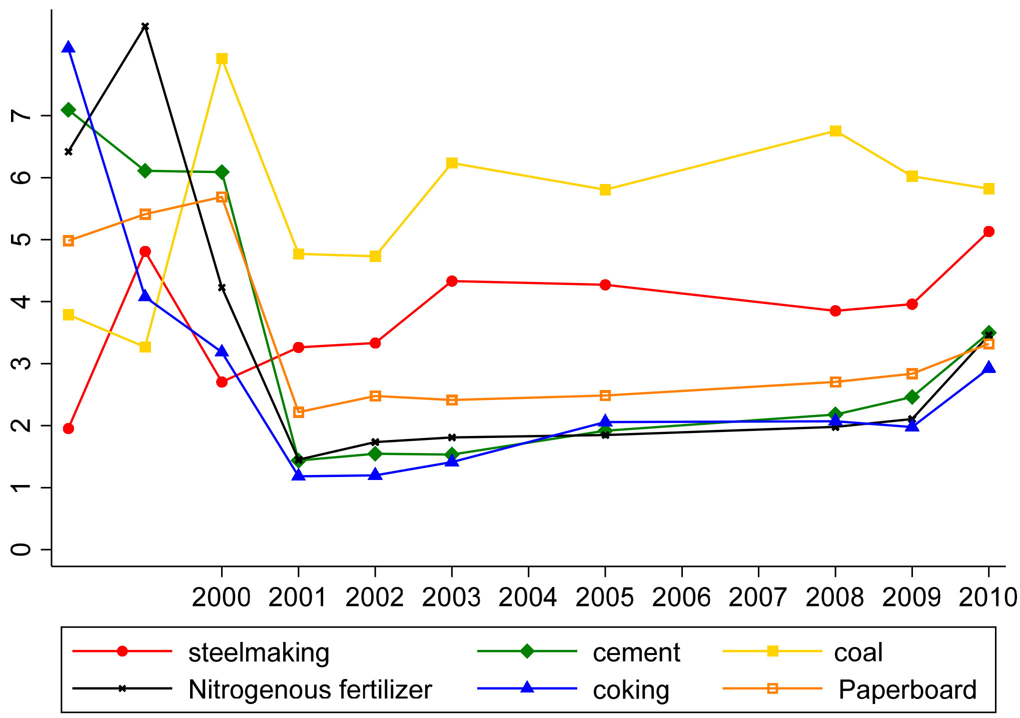

Figure 2. Heterogeneity of TPI across different industries.

4. Factors Influencing Enterprise Carbon Emission Efficiency

4.1. Model Construction

To analyze the driving factors of TPI in industrial enterprises, this paper utilized samples generated from a comparison between the China Industrial Enterprises Database and the Polluting Enterprises Database. This approach enabled a deeper understanding of the differences in TPI among enterprises within various industries. The characteristics and behaviors of industrial enterprises, along with regional factors such as geographical location and economic development, can significantly affect their TPI. Consequently, the aim of this study is to explore the factors that influence the carbon dioxide emission efficiency of industrial enterprises at both the company and regional levels. The econometric model constructed for this purpose is as follows:

$$Ln(\mathrm{TPI}_{i,j,k,t}) = \beta \mathrm{X}_{i,j,k,t} + \alpha_i + \lambda_{j,t} + \mu_{k,t} + \varepsilon_{i,j,k,t} \quad (2)$$

In the above formula, $\mathrm{TPI}_{i,j,k,t}$ represents the TPI of enterprises i in j industry in k province in t year, $Ln(\mathrm{TPI}_{i,j,k,t})$ is its logarithmic value, $\mathrm{X}_{i,j,k,t}$ is the core explanatory variable, β is the coefficient of the core explanatory variable, α_i is the constant term, $\lambda_{j,t}$ is the industry and time effect, $\mu_{k,t}$ is the regional and time effect, and $\varepsilon_{i,j,k,t}$ is the random error term.

4.2. Variable Selection

Dependent variable (TPI): The results calculated in Section 3 were utilized. For the selection of explanatory variables, this paper drew upon the findings of the related literature and selected enterprise size, coal consumption, enterprise profit, export delivery value, and total factor productivity as explanatory variables. The explanations for each are as follows:

Enterprise size (zczj): Carbon emissions are significantly influenced by an enterprise's size. A larger scale can lead to a more pronounced scale effect, lower cost per unit of output, and lower carbon intensity per unit of output. This paper measures enterprise size by the logarithm of total assets. Coal consumption(lncoal): China derives approximately 70% of its energy from coal, and the structure of its energy consumption has not significantly changed, as there has been no significant substitution of different energy sources. Therefore, the quantity of coal consumed by Chinese industrial enterprises can serve as a good indicator of their energy input. Enterprise profit (lnprofit): An increase in enterprise profit may promote employee motivation and innovation, improve production efficiency, encourage the adoption of environmentally friendly technology and management practices by enterprises, reduce carbon emissions, and create favorable conditions for improving TPI. Export volume (lnckihz): Numerous studies have confirmed that exports can enhance enterprise productivity. This enhancement is primarily achieved through competition mechanisms, technology spillover mechanisms, demonstration mechanisms, and reverse incentive mechanisms. In this paper, export delivery value is used as a measure. Total factor productivity (tfp): An increase in total factor productivity contributes to an improvement in energy efficiency and, therefore, a reduction in carbon dioxide emissions. See Table 1 below with descriptive statistics for the variables.

Table 1. Descriptive statistics of variables.

Variable	Obs	Mean	Std. Dev.	Min	Max
lneff	145,000	4.009	2.113	−0.815	11.017
lnzczj	145,000	10.696	1.654	0	18.81
lncoal	126,000	7.389	2.067	−0.336	16.109
lnprofit	109,000	7.411	2.324	0	16.563
lnckjhz	145,000	2.548	4.393	0	17.245
tfp	144,000	4.684	1.859	−7.666	12.706

Note: Obs is the number of samples, Mean is the average, Std. Dev. is the standard deviation, Min is the minimum, and Max is the maximum.

4.3. Basic Regression

Tables 2 and 3 report the regression results for samples from all industrial sectors and high-energy-consuming industries, respectively. The main explanatory variables and enterprise TPI are significantly correlated, with regression coefficients consistent with expectations.

Table 2. Stepwise regression results of industrial enterprise TPI.

	(1) lneff	(2) lneff	(3) lneff	(4) lneff	(5) lneff
lnzczj	0.204 ***	0.287 ***	0.190 ***	0.189 ***	0.138 ***
	(34.863)	(71.469)	(39.967)	(39.842)	(36.496)
lncoal		−0.866 ***	−0.908 ***	−0.909 ***	−0.912 ***
		(−252.150)	(−232.288)	(−232.727)	(−294.410)
lnprofit			0.105 ***	0.105 ***	0.052 ***
			(51.283)	(51.131)	(31.231)
lnckjhz				0.012 ***	0.008 ***
				(10.130)	(8.640)
tfp					0.571 ***
					(170.605)
_cons	1.798 ***	7.160 ***	7.930 ***	7.921 ***	6.065 ***
	(28.531)	(148.907)	(144.928)	(144.886)	(135.507)
N	120,616	104,178	75,245	75,245	75,053
R^2	0.894	0.952	0.957	0.957	0.973

t statistics in parentheses. 5, *** $p < 0.01$.

In industrial enterprises, economies of scale are evident from the size of the enterprise. This indicates that the size of an enterprise has a significant positive impact on the comprehensive efficiency of carbon emissions. Energy efficiency can be enhanced by upgrading equipment, which often requires substantial investments in fixed assets. Only larger-scale enterprises have the financial capability to afford such expensive equipment. Under financial constraints, some small- and medium-sized enterprises maintain basic production without the luxury of advanced equipment, leading to lower energy efficiency and higher carbon emissions. Conversely, enterprises with high carbon dioxide emissions are predominantly found in industries that consume large amounts of energy, such as the metallurgical and nuclear industries. These high-energy-consuming enterprises require high-temperature environments in their production processes. Expanding production scale helps reduce heat loss, thereby saving energy. Companies with more resources can engage in circular production, which reduces carbon emissions per unit of product, thus enhancing the overall efficiency of carbon emission utilization.

Table 3. The basic regression results of TPI for industrial enterprises with different fixed effects.

	(1) lneff	(2) lneff	(3) lneff	(4) lneff
lnzczj	0.435 ***	0.505 ***	0.086 ***	0.138 ***
	(197.679)	(298.003)	(20.288)	(36.496)
lncoal	−0.913 ***	−0.908 ***	−0.865 ***	−0.912 ***
	(−651.149)	(−861.212)	(−206.546)	(−294.410)
lnprofit	0.179 ***	0.081 ***	0.133 ***	0.052 ***
	(118.529)	(68.395)	(60.725)	(31.231)
lnckjhz	0.023 ***	0.018 ***	0.002	0.008 ***
	(36.420)	(37.607)	(1.511)	(8.640)
tfp	0.188 ***	0.620 ***	0.098 ***	0.571 ***
	(125.163)	(276.039)	(64.390)	(170.605)
_cons	3.788 ***	1.615 ***	8.032 ***	6.065 ***
	(206.653)	(100.163)	(161.185)	(135.507)
N	94,907	94,907	75,053	75,053
R^2	0.843	0.913	0.950	0.973

t statistics in parentheses. 5, *** $p < 0.01$.

It is crucial to acknowledge that China's energy characteristics are marked by a coal-dominated energy consumption structure, with limited oil resources and scarce gas. Approximately 75% of the country's total energy production comes from coal, and 65% of its total energy consumption is derived from coal. By 2030, it is expected that non-fossil energy consumption will be optimized to 20%, and coal consumption will decrease by approximately 50% as a result of intensified energy structure adjustments. However, altering the coal-dominated structure of energy consumption remains a challenge. Consequently, carbon dioxide emissions are primarily caused by energy consumption based on coal. TPI significantly improves when corporate profits are high, a phenomenon that can be explained from two main perspectives: employee motivation and innovation, and social responsibility and sustainable operation. On one hand, a positive relationship exists between profits and employee motivation and innovation. This incentive mechanism involves not only material rewards but also the recognition of employees' value, thereby inspiring greater work motivation. In this context, employees are more likely to engage in innovative activities, seeking new methods and technologies to reduce carbon emissions. On the other hand, a company's reputation for social responsibility plays a crucial role. Companies known for their social responsibility are more likely to adopt environmentally friendly production technologies, thus reducing carbon emissions. In summary, high profits not only inspire employees' enthusiasm and innovative potential but also reflect a company's commitment to social responsibility and sustainable operation. These factors collectively drive companies towards more environmentally friendly and sustainable development, ultimately enhancing TPI.

Improving TPI is significantly attributed to exports. The clientele of export enterprises, often being developed countries, necessitate the continuous improvement in product quality, as these countries maintain high standards for exported goods. To enhance product quality, export enterprises frequently increase R&D investment, boost overall productivity, and strengthen market competitiveness. In the market, inefficient enterprises tend to lose their competitive edge. Higher-quality products are generally more energy-efficient, consume less energy, and emit less CO2. Moreover, by engaging in exports, enterprises can integrate into the global value chain, acquiring advanced management experience and technology through international trade, which elevates their technical level and overall productivity, and reduces energy input. Additionally, importing enterprises in developed countries aiming to meet domestic standards and consumer demand for high-quality products may transfer production equipment or provide technical guidance to exporting companies. This ensures that the exported products meet environmental and quality standards, fostering continuous technological innovation and enhanced R&D capabilities in exporting companies, which in turn promotes the production of cleaner products and thereby increases TPI.

It is possible to significantly improve an enterprise's TPI by increasing total factor productivity. Efforts to achieve high-quality economic development represent one of the feasible approaches to reducing the currently high rate of carbon emissions in the country. The primary drivers of China's economic growth are labor, capital, and energy inputs. Moreover, regarding internal mechanisms, industrial agglomeration has mediated the relationship between total factor productivity and itself. Carbon emissions efficiency can be enhanced by maximizing the benefits of scale in industrial agglomeration areas and developing clean production technologies.

4.4. Heterogeneity Test

Based on the benchmark regression, this article incorporates control variables such as regional differences and the degree of industry agglomeration to further explore the reasons behind the heterogeneity in TPI among Chinese industrial enterprises. According to column (1) in Table 4, after including regional control variables, the TPI tends to be higher in the eastern regions, while it tends to be lower in the central and western regions. A significant factor affecting the TPI of enterprises is the endowment of energy resources in different regions. Due to lower TPI, companies are more likely to select resource-rich western regions; however, in line with the 'resource curse' theory, an increased endowment of energy resources weakens enterprises' awareness of energy savings, resulting in reduced carbon emissions efficiency.

Table 4. Heterogeneity test of TPI in industrial enterprises.

	(1) lneff	(2) lneff	(3) lneff	(4) lneff	(5) lneff
lnzczj	0.138 ***	0.136 ***	0.138 ***	0.138 ***	0.138 ***
	(36.455)	(35.894)	(36.471)	(36.484)	(36.426)
lncoal	−0.912 ***	−0.912 ***	−0.913 ***	−0.912 ***	−0.912 ***
	(−294.410)	(−294.692)	(−295.636)	(−294.448)	(−294.564)
lnprofit	0.052 ***	0.052 ***	0.051 ***	0.052 ***	0.052 ***
	(31.219)	(31.375)	(30.952)	(31.252)	(31.269)
lnckjhz	0.008 ***	0.008 ***	0.008 ***	0.008 ***	0.008 ***
	(8.623)	(8.724)	(8.731)	(8.624)	(8.625)
tfp	0.571 ***	0.570 ***	0.575 ***	0.571 ***	0.571 ***
	(170.614)	(170.298)	(172.006)	(170.574)	(170.674)
dist	−0.370 **				
	(−2.095)				
hhi_gyzcz		−0.162 ***			
		(−11.278)			
soe			0.194 ***		
			(17.898)		
ind				0.197 ***	
				(4.128)	
maturity					0.002 ***
					(6.077)
_cons	6.659 ***	6.143 ***	6.040 ***	5.679 ***	6.011 ***
	(23.178)	(135.802)	(135.333)	(54.808)	(131.846)
N	75,053	75,053	75,053	75,053	75,053
R^2	0.973	0.973	0.973	0.973	0.973

t statistics in parentheses. 0, ** $p < 0.05$, *** $p < 0.01$.

Column (1) in Table 4 shows that after adding the industrial agglomeration control variable, industrial agglomeration does not play the expected role, suggesting no significant spatial agglomeration effect in the industry. This lack of agglomeration reduces the level of professional division of labor and specialization, leads to redundant investment in infrastructure, increases the wastage of energy resources, and reduces the spillover effect of technology, especially green technology. This scenario is not conducive to mutual learning among enterprises and reduces both energy efficiency and TPI.

State-owned enterprises (SOEs) are more efficient at reducing carbon emissions than other enterprises due to their greater financial capacity for research and development innovation, exhibiting higher efficiency under the same conditions, as indicated in column (3) of Table 4. Although SOEs face issues such as soft budget constraints, lack of incentives, and limited operational autonomy, the government has intensified its assessment of SOEs in recent years. This includes accelerating the construction of a unified national market and ensuring equal treatment for all enterprises in aspects like loans and energy acquisition. Especially with rising labor and other factor costs, the energy usage costs for SOEs have increased, enhancing their TPI.

The TPIs of different industries also varies significantly. The manufacturing industry exhibits a significantly higher TPI than the mining industry, as shown in column (4) of Table 4. The low efficiency of the mining industry can be attributed to its focus on primary processing products and the fact that most mining products are imported from overseas, with limited exports from China. The manufacturing industry, being labor-intensive, can boost employee efficiency and reduce carbon emissions by increasing wage levels. In contrast, the mining industry, relying more on mechanized production, experiences a relatively smaller impact on carbon emissions from wage increases, which are primarily determined by equipment and technological levels. In order to reduce carbon emissions per unit of output value, enterprises optimize production processes and maximize resource use to increase output value. As technology advances and efficient production methods are developed, large-scale manufacturing becomes more efficient at reducing carbon emissions. By increasing output value, the mining industry may be able to utilize resources more effectively and reduce carbon emissions. Through improvements in production efficiency and resource utilization, industrial enterprises can reduce carbon emissions while pursuing economic benefits.

There is a relationship between the establishment duration of different enterprises and their TPI. The longer an enterprise has been in operation, the lower its TPI, as shown in column (5) of Table 4. This trend is primarily evident in enterprises that are in their maturity or decline phases. Such enterprises usually have established mature markets with less sales pressure and often benefit from a strong brand effect. As a result, their operations are not significantly affected by outdated capacities or increased costs, leading to a lack of motivation to reduce carbon emissions and improve energy efficiency. Additionally, enterprises in the maturity and decline phases often have fixed investments in high-priced equipment, which cannot be easily replaced, resulting in lower TPI. In contrast, emerging enterprises entering the market face significant sales and competitive pressures. It is crucial for them to increase their research and development funding and adopt more advanced technologies to improve their product quality. Carbon emissions efficiency is improved as a result of heightened awareness, leading to a reduction in carbon footprint per unit of product and an overall improvement in greenhouse gas emissions.

4.5. Further Discussion

To determine the relative importance of the different factors influencing enterprise TPI, this paper has identified the factors that significantly affect enterprise TPI. Figure 2 illustrates the effects of various variables on the TPI of enterprises within the same industry between 2001 and 2010 using the Shapley value decomposition framework developed by Shorrocks [39]. This model serves as a reference for distinguishing the importance of different factors.

According to the Shapley value framework, Figure 3 presents the results of the decomposition. Among all influencing factors, coal consumption, representing the energy structure and the size of the enterprise, as the most significant factors affecting TPI within an organization. Specifically, the structure of energy consumption is the most crucial factor influencing the heterogeneity among enterprises regarding TPI. Economic growth and emission reduction represent dual demands faced by contemporary Chinese industrial enterprises. Carbon dioxide emissions tend to increase with economic growth, leading to higher energy consumption, including both fossil and non-fossil fuels. Furthermore, as China has integrated 'dual carbon' strategic goals into its comprehensive development strategy for economic, social, and ecological civilization, the industrial sector must adhere to policies aimed at reducing carbon dioxide emissions, given it is the largest source of greenhouse gases.

Enterprises that do not meet the threshold of the carbon emission trading market will seek alternative ways to improve, such as by adjusting their energy consumption profiles. One strategy for adjusting the energy structure involves increasing the proportion of clean energy in the energy consumption mix or cleaning up the energy consumption structure. Additionally, diversifying the types of energy consumed and moving away from non-clean energy sources can improve the balance of energy consumption. Theoretically, these reforms in the energy consumption structure can reduce industrial carbon dioxide emissions to some extent, thereby altering the decoupling state of the industrial economy from carbon emissions. Especially in the context of energy conservation and emissions reduction, statistics from China's National Development and Reform Commission in 2022 indicate that China's coal consumption did not decrease but instead grew by 4.3%. Meanwhile, the consumption of crude oil and natural gas declined. Coal consumption accounted for 56.2% of total energy consumption, making up more than half of the overall energy consumption.

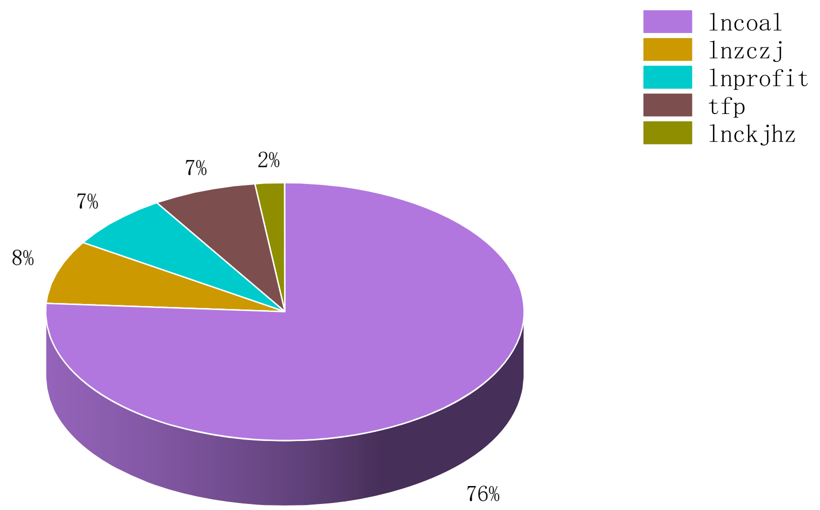

Figure 3. Impact of different factors on the TPI of enterprises in the same industry.

The scale of an enterprise significantly impacts TPI, in addition to the structure of energy consumption. The fixed costs associated with advanced technology equipment that is highly energy-efficient are typically high, which only ultra-large-scale enterprises can address. Furthermore, the expansion of production scale helps decrease energy loss in high-energy-consuming industries due to the need for high-temperature environments, which reduces heat dissipation areas. Additionally, large enterprises can improve TPI through waste heat recovery and utilization. For example, in the production of steel and cement, waste heat can be used for power generation. However, small enterprises often lack the relevant technology and equipment to recycle waste heat and energy, resulting in considerable energy loss. According to the Environmental Kuznets Curve theory, the relationship between carbon emissions and economic growth exhibits an inverted U-shaped characteristic. The size of enterprises is a manifestation of this phenomenon, which has been confirmed in numerous studies [40–42].

5. Conclusions and Policy Recommendations

Between 2001 and 2010, micro-level data from Chinese industrial enterprises within the same industry were analyzed to measure heterogeneity in Total Factor Productivity (TPI). The study finds substantial differences in TPIs within segmented industries. Industries that consume high quantities of energy, including coal mining and washing, as well as smelting and processing ferrous metals, exhibit significant disparity in TPI. The structure of energy consumption and the scale of the enterprise are identified as the two most important factors affecting TPI, suggesting a need for accelerating the energy transformation of industrial enterprises.

This research suggests that future carbon emission policies by the government should fully consider the potential impact of heterogeneity in enterprise TPI. Specific recommendations include: ① Optimizing the Energy Structure: Carbon emission policies should prioritize optimizing the energy structure, encouraging enterprises to reduce carbon emissions by increasing the use of clean energy sources, such as solar, wind, and hydropower, and reducing reliance on fossil fuels. Additionally, adopting energy recovery technologies to enhance energy efficiency and reduce waste is recommended. ② Controlling Fossil Fuel Consumption: It is crucial to control fossil fuel consumption and implement orderly coal reductions in industries such as steel, building materials, petrochemicals, and non-ferrous metals. This includes promoting efficient and environmentally friendly coal utilization by developing a modern coal chemical industry that is stable and orderly, promoting the safe and efficient use of natural gas, and supporting the development of 'photovoltaic + energy storage' and other self-supplied power plants to improve access to clean energy locally. ③ Optimizing the Capacity Scale of Key Industries: Revising the Industrial Structure Adjustment Guidance Catalog and strictly implementing capacity-replacement policies in industries such as steel, cement, flat glass, and electrolytic aluminum are advised. Overcapacity analysis, early warnings, and guidance in key industries should be strengthened, with a focus on quickly resolving excess capacity. Establishing a comprehensive standard system focused on environmental protection, energy efficiency, quality, safety, and technology is also recommended. ④ Coal Replacement in Key Areas: For new, modified, or expanded coal-using projects, the implementation of coal replacement with equal or reduced amounts of coal or other energy sources is required by law. High-pollution fuels like petroleum coke, coke, or blue coal should not be used as measures for reducing coal consumption. Improving the management methods for reducing and replacing coal consumption in key areas is essential, with support provided for existing self-supplied coal-fired units to switch to clean energy. ⑤ Considering Regional Heterogeneity in Carbon Emission Efficiency: If total carbon emission target control cannot be avoided, the heterogeneity of carbon emission efficiency between regions should be fully considered. Stricter energy-saving targets should be implemented for the eastern region and enterprises with lower carbon emission efficiency to prevent the flow of backward production capacity from efficient eastern regions to less efficient central and western regions, and from high-efficiency large enterprises to less efficient small and medium-sized enterprises. Other related carbon emission measures are outlined in Table 5.

Table 5. Carbon emission-reduction measures.

Path	Content
Source Reduction	Promote terminal electrification comprehensively, achieving source reduction
Energy Substitution	Substitute traditional fossil energy with wind, solar, energy storage, hydrogen, etc.
Energy Saving and Efficiency	Enhance energy efficiency in industries like manufacturing and construction
Recycling and Reuse	Reduce carbon emissions in initial production processes, like steel scrap, battery recycling, waste sorting, and solid waste treatment
Process Transformation	Mainly focuses on upgrades in battery technology, smart grids, distributed power sources, ultra-high voltage, energy internet, prefabricated construction, etc.
Carbon Capture and Storage	Separate carbon dioxide produced by industrial and related energy industries, then use carbon storage methods to transport and store it in places isolated from the atmosphere, like under the sea or underground

However, this paper has its limitations. Due to the availability of data, we were unable to calculate the situation after 2011. Once updated data become available in the future, we plan to extend this method to the period post-2011 to reflect the new changes and characteristics in the development trend of China's industrial carbon emissions. Since the China Pollution Enterprise Database has not been updated after 2010, further research is contingent upon its update. Moreover, this paper does not delve into the specific policies discussed towards the end due to limitations in micro-level data availability and the necessity to consider specific factors for evaluating each policy. It is hoped that this work will alert policy-making bodies and the academic community to the impact of heterogeneity in enterprise TPI on policy effectiveness, inspiring more follow-up research.

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