Enhancing Market Efficiency with AI: A Game-Theoretic Approach to Mitigating Information Asymmetry in Digital Economies

1 Introduction

China has entered the late stage of industrialization, becoming the world's first industrial and manufacturing country. The manufacturing industry's situation is significant but needs to be more robust. It still needs to be changed, and energy consumption accounts for a high percentage, which does not match the level of the value-added ratio, resulting in low efficiency in the use of energy. By the end of 2021, China's manufacturing industry's total energy consumption and carbon emission accounted for two-thirds of the secondary sector. China's Fourteenth Five-Year Plan plans an "in-depth implementation of the strategy of manufacturing a strong country" to promote the high-quality development of the manufacturing industry, the development of China's manufacturing industry in the new stage of development, precise new requirements, and strategic focus. Realizing resource-saving and environmentally friendly green manufacturing is an essential issue for the high-quality development of the manufacturing industry. Under the goal of "carbon peaking and carbon neutrality," the manufacturing industry, as a significant sector in terms of energy consumption and carbon emissions, will face considerable challenges."The Fourteenth Five-Year Plan calls for the proportion of the manufacturing sector to remain stable and to avoid "premature deindustrialization".Under the pressure of these two goals, improving energy efficiency in manufacturing has become essential to realize the win-win situation of green manufacturing and growth.

China's vast territory, the regional economic development differences, and the evolution of the law of the manufacturing industry energy efficiency in various regions also present complexity and regional heterogeneity. If the advanced areas of manufacturing energy technology can be effectively diffused, backward areas of manufacturing efficiency show a catch-up effect; it will significantly improve China's overall manufacturing energy efficiency. This is also an essential issue for China's manufacturing industry's high-quality development and narrowing regional disparities.The purpose of this paper is to carry out the evaluation of China's provincial manufacturing energy efficiency under environmental constraints and to explore the regional variability and catch-up effect of China's manufacturing energy efficiency, which plays an essential role in improving China's manufacturing energy efficiency as a whole and is also one of the critical issues for the high-quality development of China's manufacturing industry.

2 Literature review

2.1 Energy efficiency

There are usually two ways to measure energy efficiency: one is single-factor energy efficiency, which only accounts for the relationship between individual outputs and energy inputs, such as the energy intensity indicator, which is simple to calculate, widely adopted by scholars, and often used as a standard for formulating energy policies (LIU et al., 2019). This method does not take into account the substitution between different factors of production, usually overstates energy efficiency, and is therefore unsuitable for measuring energy efficiency in multi-input, multi-output scenarios (DU et al., 2018). The other is Total Factor Energy Efficiency (TFEE), which is widely recognized and used because it incorporates labor and capital into the analysis under the framework of neoclassical production theory, takes into account the substitution effects between energy and other factors of production, and can measure energy efficiency in a more comprehensive way (YU et al., 2021).

In this framework, energy efficiency is the ratio of optimal and actual energy inputs.The energy efficiency defined by (HU&WANG, 2006) is a radial measure, i.e., all inputs are required to be scaled down in the same proportion.The method does not isolate the inefficiencies of other factors of production, so (BOYD, 2008) defines an energy distance function reacting to the degree of deviation from the optimal energy inputs in the direction of the energy inputs. In the existing literature, total factor energy efficiency is usually measured with the help of production frontier analysis techniques, which typically include the data envelopment analysis (DEA) method and the parametric stochastic frontier analysis (SFA) method. Inefficiency measurement, SFA is more complicated in terms of the basic assumptions of the model, which requires the establishment of a production function and the specific setting of the distribution of technical inefficiencies. In contrast, the DEA does not make specific strict requirements on the production frontier and does not require particular assumptions on the input-output function. The analysis in this paper is built under the framework of total factor energy efficiency analysis (DEA).

With the importance of environmental regulation in recent years, most scholars have taken non-expected outputs into account and have widely adopted the co-production framework. Most of the above literature on analyzing energy efficiency in the manufacturing industry introduces non-expected outputs. In terms of the development history of research methods, the directional distance function (DDF) proposed by (CHUNG et.al., 1997) was first widely used to dispose of non-expected outputs. However, this method requires that the reduction in non-desired production is the same proportion as the increment of desired output, which is a radial measure. Considering the slackness of input-output variables, (Tone, 2001) proposed the SBM model. (Fukuyama &Weber, 2009), on the other hand, combined the ideas of the SBM and the DDF and proposed a non-radial, non-angle DEA method, the SBM (Slack-based Measure) directional distance function. (Zhou et al., 2012)'s SBM_DDF method does not formally define the function and proposes a non-radial distance function instead of the SBM method.This approach has been widely applied and expanded in the measurement of energy efficiency (ZHANG et.al., 2014; ZHANG&SONG, 2020;SHI et.al., 2022; MA et.al., 2023).

2.2 Energy Efficiency in China's Manufacturing Sector

A growing number of scholars have focused on energy efficiency in China's manufacturing sector. A subset of scholars study manufacturing energy efficiency from an industry perspective. (Qu et al., 2016) used the 2003-2013 Chinese manufacturing industry panel data as a sample, using the SBM model to study the total factor energy efficiency of manufacturing industry under environmental constraints and its influencing factors; (Wang & HAN, 2017) used the SBM model to model the energy efficiency of China's 29 manufacturing industries from 2006-2011, and the results showed that the energy efficiency of each sector was steadily improving year by year, and the energy differences between industries were significant; (Lu et al.,2019) measured the total factor productivity of the manufacturing industry and its three types of energy-consuming industries based on panel data from 2003-2013, using the DEA-Malmquist productivity index decomposition method. (Li et al., 2019) constructed the SBM model to measure the energy eco-efficiency of manufacturing industry in 30 provinces and municipalities in China in the period of 2000-2016. Regional differences in manufacturing eco-efficiency are analyzed. Individual scholars, such as (Chen et al., 2021) considered the dual perspectives of regions and sub-sectors and used the SBM model to measure the total factor energy efficiencies of 19 manufacturing sub-sectors in 9 provinces in China from 2001 to 2011 and explored the differences in energy efficiencies between light and heavy industries. (Lin & GUAN, 2023) used the global DEA method and non-radial directional distance function to measure the unified efficiency index of 28 provinces and 27 sub-sectors in China's manufacturing industry. As the research progresses, some scholars specifically discuss the impact of market reform (Zhou & Li, 2021), technological progress(CHEN & LIU, 2021), open channels (WEI et al., 2020), infrastructure (CHEN & LIN, 2021), and industrial convergence (DONG et al., 2021) on the energy efficiency of China's manufacturing sector.

2.3 Variance and convergence analysis of energy efficiency

The existing literature analyses the distributional characteristics of energy efficiency as well as spatial variations, mainly by kernel density estimation (WU, 2023; CHENG et al., 2020), and by methods such as the coefficient of variation, the Thiel index(FENG et al., 2016), and the Dagum Gini coefficient (ZHAO, 2024). In terms of convergence of energy efficiency, it mainly includes σ-convergence, β-convergence test, and club convergence of energy efficiency (YU et al., 2018; OUYANG et al., 2021; LV et al. , 2017; HE & CHEN, 2022). Existing literature needs to pay more attention to the regional differences in energy efficiency and the convergence aspect of China's manufacturing industry. (Liu, 2022) measured and analyzed the evolutionary trend of energy carbon emissions and their efficiency in manufacturing based on the panel data of 10 sub-sectors in China's manufacturing industry. Scholars have not yet analyzed the convergence or catch-up effects of energy efficiency in China's provincial manufacturing industries.

This study mainly extends the existing research in the following aspects. Firstly, it accounts for the manufacturing energy consumption of each province in the collection of sample data, avoiding the use of industrial energy consumption instead of manufacturing energy consumption similar to similar literature; secondly, this study pays attention to the regional differences and catch-up effects of China's manufacturing energy efficiency for the first time, which is of great significance for the optimization of manufacturing high-quality development policy design and assessment. Finally, this study constructed a TFP catch-up model (BERNARD et al., 1996) to analyse, which simultaneously shows the technology spillover effect and the productivity catch-up speed.

The remainder of this paper is organized as follows: part II introduces the materials and methods; Part III empirically estimates the manufacturing energy efficiency of Chinese provinces and presents the results; Part IV explores regional differences in energy efficiency in China's manufacturing sector; part V constructs a TFP catch-up model of manufacturing energy efficiency in China.Part IV contains conclusions and recommendations.

3 Model establishment and data

3.1 Environmental Production Technology for Manufacturing

Under the assumption of weak disposability and zero-combination of non-desired outputs, following the analytical framework of (FÄRE et al., 2007), assuming that there are N provinces and that the manufacturing industry in each of them has three input factors of capital (K), labor (L), and energy (E) co-produced, and that the desired outputs are the total output value of the manufacturing industry, Y.The non-desired outputs are B, which is calculated by using a comprehensive indicator of industrial three wastes.Then the environmental production technology can be expressed as the following set:

$$T = \{(\mathrm{K}, \mathrm{L}, \mathrm{E}, Y, B) : \mathrm{K}, \mathrm{L}, \mathrm{E} \text{can produce } (Y, B)\} \tag{1}$$

Where T is to satisfy the following two axioms:

1. If (K,L,E,Y,B) $\in T$ and $0 \leq \theta \leq 1$, them (K, L, E, θY, θB) $\in T$. That is, non-desired outputs are weakly disposed of, and reducing non-desired outputs requires reducing desired outputs.

2. If (K,L,E,Y,B) $\in T$ and B=0, then Y=0. That is the null hypothesis, which suggests no desired outputs without non-desired outputs.

The DEA approach can be used to build this environment production technology set as follows:

$$T = \begin{cases} ((\mathrm{K}, \mathrm{L}, \mathrm{E}, Y, B) : \sum_{n=1}^{N} Z_n K_n \leq K, \sum_{n=1}^{N} Z_n L_n \leq L, \sum_{n=1}^{N} Z_n E_n \leq E, \\ \sum_{n=1}^{N} Z_n Y_n \geq Y, \sum_{n=1}^{N} Z_n B_n = B, n = 1 \dots N \end{cases} \tag{2}$$

3.2 Non-radial Direction Distance Function

Chung proposed the directional distance function for efficiency measurement, which can increase outputs and simultaneously reduce inputs on the path of the directional vector set by the researcher. As a radial measure with desirable mathematical properties, the directional distance function (DDF) has achieved wide application in energy efficiency (SONG & WANG, 2018). The traditional DDF is a radial efficiency measure, which may overestimate the efficiency when there are certain slack variables (FUKUYAMA & WEBER, 2009). Non-radial efficiency measures are often advocated to overcome this limitation in measuring energy and environmental performance due to their advantages (FEI & LIN, 2017).

To solve the problem that the directional distance function fails to solve the problem of non-zero relaxation variables, (Zhou et.al., 2012) extends it to a non-radial directional distance function, and according to its idea, we precisely define the non-radial directional distance function of the provincial manufacturing industry as:

$$\vec{D}(K, L, E, Y, B; g) = \sup\{\omega^T \beta : (K, L, E, Y, B) + \mathrm{diag}(\beta) \cdot g \in T\} \tag{3}$$

Where ω=(ω_K,ω_L,ω_E,ω_Y,ω_B) is the weight variable of each variable, which sums to 1; g=(-g$_K$,-g$_L$,-g$_E$,-g$_Y$,-g$_B$) is the directional vector; and β=(β_K, β_L, β_E, β_Y, β_B) ≥ 0 is the shrinkage (expansion) factor of each input-output variable, representing the non-efficiency value. Inputs and outputs can be varied in different proportions, overcoming the radial problem of the directional distance function. Then $\vec{D}$(K,L,E, Y,B:g) is the maximum shrinkable (expansion) ratio, which reflects the extent to which the DMU deviates from the efficient production boundary. The directional vector can generally be set according to different policy objectives.

The value of $\vec{D}$(K,L,E, Y,B; g) can be solved by the DEA method, whose linear programming can be written as:

$$
\begin{aligned}
&\vec{D}(K, L, E, Y, B; g) = \max \omega_K \beta_K + \omega_L \beta_L + \omega_E \beta_E + \omega_Y \beta_Y + \omega_B \beta_B \\
&s.t. \sum_{n=1}^{N} Z_n K_n \leq K - \beta_{KgK}, \\
&\sum_{n=1}^{N} Z_n L_n \leq L - \beta_{LgL}, \\
&\sum_{n=1}^{N} Z_n E_n \leq E - \beta_{EgE}, \\
&\sum_{n=1}^{N} Z_n Y_n \leq Y - \beta_{YgY}, \\
&\sum_{n=1}^{N} Z_n B_n \leq B - \beta_{BgB}, \\
&Z_n \geq 0, n = 1, 2, \ldots N, \\
&\beta_K, \beta_L, \beta_E, \beta_Y, \beta_B \geq 0
\end{aligned}
\tag{4}
$$

where Z_n is the weight of each DMU, which can be set to different direction vectors g according to different policy goals.If $\vec{D}$(K,L,E,Y,B; g)=0,then this DMU lies on the technology frontier under the given direction of g.

3.3 Definition of energy efficiency index under Environmental Constraints

In order to measure the energy efficiency of the manufacturing industry under environmental constraints, following (Zhang et al., 2013c), non-energy inputs are fixed considering that energy inputs are the main contributor to emissions, while other factors of production do not directly contribute to emissions. Therefore, the direction vector is set as g=(0,0,-E,Y,-B), the weights are set as ω=(ω_K,ω_L,ω_E,ω_Y,ω_B)=0,0,1/3,1/3,1/3 since there are three input variables, both desired and non-desired outputs are one variable. Construct the energy-environment NDDF and obtain the most linear programming solution β_E^*, β_Y^*, β_B^* and define the manufacturing energy efficiency index under environmental constraints as follows:

$$
EEPI = \frac{1/2[(1 - \beta_E^*) + (1 - \beta_B^*)]}{1 + \beta_Y^*} = \frac{1 - 1/2(\beta_E^* + \beta_B^*)}{1 + \beta_Y^*} \tag{5}
$$

The manufacturing energy efficiency index under environmental constraints calculated in this paper, i.e., EEPI, is hereafter referred to directly as manufacturing energy efficiency for simplicity.

3.4 Sample selection and grouping

To explore the changes in the energy efficiency index of China's manufacturing industry in recent years and to make inter-provincial comparisons, given the availability and timeliness of the data, the panel data of 30 provinces, municipalities, and autonomous regions (excluding Hong Kong, Macao, and Taiwan) in China from 2011 to 2021 are selected as samples.

Taking into account the technical heterogeneity of China's regions, with China's economic development, the direct geographical imbalance intensifies, the industrial structure, demographic conditions, and the gap in technological level between the provinces gradually widen, the original East, Central, West, Northeast, and other divisions of the law has been out of date.This paper is based on the 2005 release of the "Strategies and Policies for the Coordinated Development of Regions", which divides the country into eight economic regions, mainly as shown in Tables 1.

Table 1: Division of China's economic regions

Economic Zone Category	Results
North Coastal Region	Beijing, Tianjin, Hebei, Shandong
East Coastal Region	Shanghai, Jiangsu, Zhejiang
South Coastal Region	Fujian, Guangdong, Hainan
Northeast Region	Liaoning, Jilin, Heilongjiang
Middle reaches of the Yellow River Region	Inner Mongolia, Shanxi, Shaanxi, Henan
Middle reaches of the Yangtze River Region	Anhui, Hubei, Hunan, Jiangxi
Northwest Region	Gansu, Qinghai, Ningxia, Xinjiang
Southwest Region	Guangxi, Yunnan, Guizhou, Sichuan, Chongqing

3.5 Selection and Description of Indicators

The non-radial distance function model based on DEA is considered from the input-output perspective concerning the indicators used more frequently by previous scholars, and the indicators are described as follows:

(1)Input indicators

Capital investment (K): Most of the literature on the measurement of capital stock as a proxy variable and reference to the perpetual inventory method, which requires the base period of the capital stock and the appropriate depreciation rate.Limited to data availability,this paper selects the manufacturing industry's annual net fixed assets (100 million yuan) to express the capital inputs, the source of data for the past years of China's Industrial Statistical Yearbook of the manufacturing industry grouped by region of the leading economic indicators. The data were deflated using each province's fixed asset investment price index.

Labor Input (L): For labor input, the average number of workers employed per year in each province is chosen. The data source is the "Major Economic Indicators of Manufacturing Industry by Regional Grouping" of the China Industrial Statistical Yearbook of the past years.

Energy Consumption (E): This is expressed by the manufacturing industry's comprehensive energy consumption (tons of standard coal), which is mainly replaced by the gross industrial output value in the previous literature on the energy efficiency of the manufacturing industry in the province.

This paper has done a lot of work on the collection of energy consumption of the manufacturing industry in various provinces and cities due to the lack of uniformity of statistical indicators in the provinces in the statistics of energy consumption, mainly for the following cases are dealt with separately:

First, there are direct statistics on comprehensive energy consumption in manufacturing industries, such as Beijing, Shanxi, Inner Mongolia, Jiangxi, Guangdong, Guangxi, Guizhou, Yunnan, Gansu, Qinghai, Ningxia and Xinjiang.

Secondly, it is possible to calculate the ratio of manufacturing and industrial energy consumption (or total energy consumption) based on categorized energy consumption and then multiply it by the corresponding industrial energy consumption (total energy consumption), e.g., Tianjin, Liaoning, Jilin, Heilongjiang, Hunan, Shaanxi.

Thirdly,The energy consumption of the above-scale manufacturing industry is calculated based on the energy classification consumption. Then,the total energy consumption of the manufacturing industry is inferred based on the ratio of the total consumption of the above-scale sector to the total industrial energy consumption. e.g., Hebei, Fujian, Henan, Hainan, and Chongqing.

Fourthly,Some provinces only counted the total energy consumption of the manufacturing industry in some years, and then first estimated the ratio of the manufacturing energy consumption to the total industrial energy consumption in the province, and then projected the energy consumption of the manufacturing industry in other years, e.g., Shanghai, Shandong, and Sichuan.

The source of the data is the energy section of the provincial statistical yearbooks. Some provinces, such as Tianjin, did not summarize the consumption of various energy sources but converted it to standard coal according to the standard coal conversion coefficients of different energy sources.

(2)Expected output indicators

Manufacturing output (Y): The manufacturing output of each province is used as the expected output. The missing data from individual provinces, such as Liaoning and Tianjin, are replaced by manufacturing operating revenue. The data are deflated using the producer price index for each province.The source of data is the Industrial Statistics Yearbook for each year.

(3)Indicators of non-expected outputs

Industrial three wastes (B:) Since it is difficult to obtain the emissions of manufacturing industries in each province separately, "industrial three wastes" (industrial emissions of gas, wastewater, and solid wastes) are chosen to measure the non-desired outputs. Because of the large number of total categories of non-desired outputs, the entropy weight method was used to synthesize a single indicator B for calculation.The source of data is the Industrial Statistics Yearbook for each year.

4 Measurement and Analysis of Energy Efficiency in China's Manufacturing Industry

4.1 Measurement results of manufacturing energy efficiency in China's provinces

As shown in Figure 1, In terms of provinces, Beijing has been at the forefront of manufacturing energy efficiency. At the same time, Guangdong has seen a significant improvement in manufacturing energy efficiency after 2017, ranking second in the entire interval. Jiangsu, Shanghai, and Zhejiang come next, and these mainly stem from the large proportion of high-tech manufacturing in these provinces and the high energy efficiency of the industry. Regarding the timeline, manufacturing energy efficiency in most provinces shows a short-term fluctuating general improvement trend (most provinces showed a decline in manufacturing energy efficiency in 2018 after China conducted an economic census output value adjustment).On the other hand, Liaoning Province suffered a sharp decline mainly because of its heavy energy structure and strong dependence on energy consumption for economic growth, coupled with ineffective "dual control" of energy consumption. According to statistics, its comprehensive energy consumption in industries above the designated size in 2020 increased by 22.7 percent compared with 2018. Among them, the integrated energy consumption of the six major high-energy-consuming sectors rose by 27 percent compared with 2018.

Regionally, the East Coastal region has a higher overall level and a more even internal development, followed by the South Coastal and the North Coastal, with the South Coastal benefiting mainly from the significant improvement in manufacturing energy efficiency in Guangdong and Fujian in recent years. Overall, manufacturing energy efficiency in coastal regions is higher than inland regions.However, it can be seen that the middle and lower reaches of the Yangtze River have seen a significant increase in manufacturing energy consumption. The downward trend in manufacturing energy efficiency in the Northeast is mainly due to Liaoning Province.The manufacturing energy depression is still mainly in the west, in which the Northwest region has the lowest level of manufacturing energy efficiency, mainly due to the relatively large proportion of energy-consuming industries.

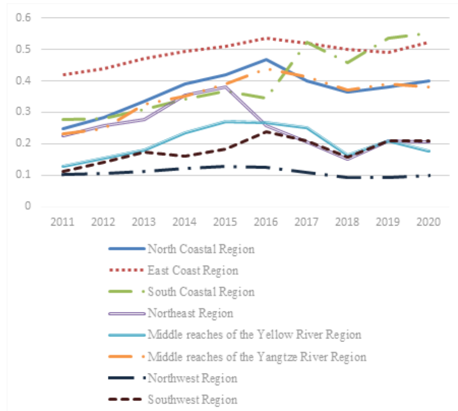

Figure 1: Trends in manufacturing energy efficiency in eight regions, 2011-2020

4.2 Energy Efficiency Differences in China's Manufacturing Industry and Their Decomposition

Usually, the degree of inequality is measured by indicators such as the Thiel index and the classical Gini coefficient to solve the problem of possible cross-over in grouped samples. In this paper, the Dagum Gini coefficient method is used to measure the overall differences, regional differences, inter-regional differences, and hyper-variable density of manufacturing energy efficiency in the eight economic zones of China. According to the definition of Dagum's Gini coefficient, equation (8) is the formula for the overall Gini coefficient G (DAGUM, 1997):

$$G = \frac{\sum_{j=1}^{k}\sum_{h=1}^{k}\sum_{i=1}^{n_j}\sum_{r=1}^{n_h}|Y_{ji}-Y_{hr}|}{2n^2\bar{Y}} \tag{6}$$

Where j and h are subscripts of economic zones, i and r are subscripts of provinces, k denotes the number of economic zones 8, $n_j(n_h)$ is the number of provinces within economic zone j(h), $Y_{ji}(Y_{hr})$ represents the manufacturing energy efficiency of province and city i(r) within economic zone j(h), denotes the average of the manufacturing energy efficiency of all provinces, and n represents the number of all provinces. Before the decomposition, firstly, the eight economic zones' energy efficiency averages are ranked as $\bar{Y_{j1}} \leq \bar{Y_{j2}} \leq \bar{Y_{j3}} \leq \cdots \leq \bar{Y_{j8}}$. Then, the overall Gini coefficient is decomposed into three components: intra-region variation contribution (G_w), inter-region variation contribution (G_{nb}), and hyper-variable density contribution G_t, which satisfy the relationship equation $G{=}G_w{+}G_{nb}{+}G_t$.

The specific calculation formula will not be repeated.

The primary source of the overall Gini coefficient is hyper-variable density, as seen quite intuitively in Figure. 2. Although the contribution rate of hyper-variable density has declined in recent years, it is stable at 70 percent, indicating

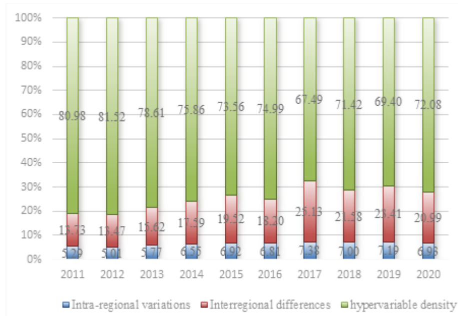

Figure 2: Spatial Gini coefficient decomposition for eight regions

more cross-layering of manufacturing energy efficiency among regions. For example, in several coastal areas, manufacturing energy efficiency cross-layering is more. The second largest contributor is the between-group variation, which shows an overall increasing trend of about 20 percent, with a slight decrease in recent years. The contribution of inter-regional variations is the smallest, with a slight tendency to increase but remaining stable at around 7 percent in recent years.

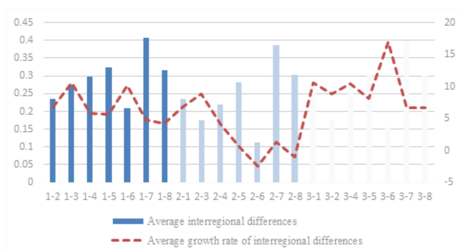

Figure 3: Average difference between the three coastal regions and the rest and their average growth rates (%)

Due to space constraints Figure. 3 only shows the average difference between the three major coastal regions and the other regions from 2011-2020, as well as the average rate of change. Except for the average rate of change of the difference between the East coastal and the Middle reaches of the Yangtze River and the Southwest region, which is negative, all other average rates of change are positive, indicating that the difference between the coastal region and the other regions is expanding, with the North Coastal region having a more significant difference with the different regions.

5 Analysis of Energy Efficiency in China's Manufacturing Industry

5.1 Energy efficiency catch-up model for China's manufacturing sector

Since the Gini coefficient of energy efficiency in China's manufacturing industry is growing slowly and the gap between regions is increasing, is there a technology diffusion from frontier regions and a catching-up effect from lagging areas in China's manufacturing energy efficiency? For this purpose this paper draws mainly on the TFP catch-up model proposed by Bernard and Jones and examines the convergence of energy efficiency in the manufacturing sector within this framework. In this model, the energy efficiency level of a sample depends on the energy efficiency of the previous period as well as the energy efficiency levels of the current and prior periods of the efficiency frontier, i.e., the evolution of energy efficiency follows the autoregressive distributed lag ADL (1, 1) process, based on which the following energy efficiency productivity catch-up model in China's provincial manufacturing industry is constructed.

$$lnEEPU_{it} = \alpha_1 \ln EEPI_{it-1} + \alpha_2 \ln EEPI_{Ft} + \alpha_3 \ln EEPI_{Ft-1} + \pi X_{it} + u_{it} \quad (7)$$

The long-run equilibrium assumption ($\frac{\alpha_2+\alpha_3}{1-\alpha_1}$=1) ensures that the rate of productivity catch-up depends on the relative rather than the absolute level of productivity, which in turn yields the following equilibrium corrected model (ECM) .

$$\triangle \ln EEPI_{it} = \alpha_2 \triangle \ln EEPI_{Ft} + \lambda \ln(\frac{EEPI_{Ft} - 1}{EEPI_{it} - 1}) + \pi X_{it} + u_{it} (\lambda = 1 - \alpha_1) \quad (8)$$

In $\triangle \ln EEPI_{Ft}$ this model, $\triangle \ln EEPI_{it}$ is the manufacturing energy efficiency growth rate of province i in year t. denotes the movement of the energy efficiency frontier in period t (which can be regarded as technological progress) and ln $\frac{EEPT_{Ft-1}}{EEPI_{it-1}}$ represents the gap between the manufacturing energy efficiency of the province i and the frontier in period t-1, which can be defined as Gapit-1, with the more significant value indicating the more significant gap between the energy efficiency of the manufacturing sector and the production frontier in the province.

From this model (8) can be expressed as

$$\triangle \ln EEPI_{it} = \alpha_2 \triangle \ln EEPI_{Ft} + \lambda G_{ap_{it-1}} + \tau X_{it} + u_{it} \quad (9)$$

Where λ and α_2 are the focus of attention in this paper. The coefficient λ describes the catching-up effect of technology diffusion. if λ>0 , it means that the lower the energy efficiency of the manufacturing industry in the last period, the more significant the gap with the production frontier surface of the sample in the current period of the energy efficiency growth rate. α_2 measures the efficiency frontier's pull on the other provinces' energy growth rate, which can be considered as a direct effect of technology diffusion. Both $\triangle \ln EPI_{it}$ and Gap_{it-1} contain EPI_{it-1}, so the two have a direct bi-directional causal relationship. Thus, there is an endogeneity problem with the explanatory variable Gap_{it-1}; thus, it is biased to take OLS estimates. This paper adopts generalized moment estimation to address the issue of endogenous bias and to take into account within-group heteroskedasticity and autocorrelation. It uses lagged terms of variables as instrumental variables. The lagged term of the variable avoids the existence of joint causality and thus ensures that the instrumental variable is reasonable.

The model of energy efficiency catching up in China's manufacturing industry is constructed in Table 4 because the efficiency frontier growth rate (mg) variable is a variable that varies with the year and, therefore, cannot be included in the year effect or else it will result in multiple covariances, so this paper introduces the m2 growth rate as well as the uncertainty of the policy (epu) instead of the year effect. The results in the first column show that the efficiency frontier growth rate (mg) is highly significant, indicating a considerable technology diffusion effect in the national efficiency frontier. The coefficient of energy efficiency gap (GAP) is significant, meaning the catching-up impact on the efficiency frontier is substantial and the provincial manufacturing energy efficiency has absolute convergence characteristics.

In the second and third columns, following the method of introducing multiple frontiers (GONG, 2022),this paper presents the regional frontier. In contrast, column 2 adds the regional frontier efficiency growth rate (mgr) and the regional frontier gap (GAPR) based on column 1. While in column 3, only the regional frontier efficiency growth rate (mgr) and the regional frontier gap (GAPR) are considered. The results in column 2 show that the regional frontier energy efficiency gap (GAPR) is insignificant. The other three variables are all highly significant, indicating that the province's catching-up effect on the regional frontier is insignificant. In contrast, the catching-up impact on the national frontier is significant. The technology spillover effects of the national efficiency frontier and the regional frontier are substantial. A comparison of the regression results in columns 1 and 3 shows that the national efficiency frontier has a more significant impact. This also indicates that the diffusion and catch-up of energy technologies in manufacturing are less affected by spatial distance.

The conclusion shows that in the area of energy efficiency in China's manufacturing sector, the technological spillovers from the national efficiency frontier and the catching up to the nationwide technological frontier are higher than the role of the geographically neighboring frontier. Therefore, only the national frontier is used in the subsequent studies in this paper.

In column 4, the energy efficiency gap (GAP) variable is discarded. Instead, the energy efficiency of manufacturing industries in each province of the country is divided into five levels. A quantile dummy variable is introduced to indicate the gap with the frontier, with GAP5 denoting the level with the most significant gap with the frontier. The introduction of quartiles circumvents the problem of variable endogeneity, and the results in column 4 show that the coefficients of GAP2-GAP5 are increasingly large and highly significant, which confirms the validity of the conclusion in column 1 that the more significant the gap from the national efficiency frontier, the more influential the catching-up effect.

5.2 Convergence model of manufacturing energy efficiency in eight regions of China

The productivity catch-up models for the eight regions in the country are constructed and compared using the national efficiency frontier along the lines of the above findings.From the results in Table 5, absolute convergence characteristics of manufacturing energy efficiency are inconsistent across regions. Specifically, the middle reaches of the Yellow River and the middle reaches of the Yangtze River have relatively significant manufacturing energy catch-up efficiency and frontier technology diffusion effects.The North Coastal, Northeast, and Northwest regions have rather significant catch-up effects but insignificant frontier technology diffusion effects, while the east coastal, south coastal, and southwest regions have insignificant manufacturing catch-up and frontier technology diffusion effects. This also explains the widening regional differences in energy efficiency in our manufacturing sector.

5.3 Energy Efficiency Catch-up Model for China's Manufacturing Industry with the Addition of Control Factors

The introduction of controls in the model was considered to analyze other influences on the growth of manufacturing energy efficiency in the provinces. Considering the limited sample size of the sub-region, which affects the regression quality, this section is analyzed only based on the national manufacturing energy efficiency catch-up model. Based on previous studies, the provincial control variables in this paper are mainly selected:

(1) Each province's economic development level is expressed in GDP per capita.

(2) The degree of openness, measured by the proportion of actual foreign capital use to GDP in each province.

(3) Level of technological innovation, measured by the ratio of R&D expenditure to regional GDP in each province.

(4)The level of advanced manufacturing industry structure. Following the example of (Fu, 2014) , who merged high-end and mid-high-end technology industries, the manufacturing industry is divided into three categories, and the ratio of the output value of high-end industry output value of the mid-end sector is used to indicate the heightened industrial structure of the manufacturing industry in each province;

(5)Percentage of energy-intensive manufacturing industries. They are expressed using the ratio of the output value of the six major energy-intensive manufacturing industries to that of the manufacturing industry in each province.

(6) Energy consumption structure, measured by the ratio of coal consumption to total energy consumption in each province.

(7) Environmental regulation, measured by the ratio of pollution control investment to industrial value (CHEN et al., 2022).

Similar to the previous section, GMM-robust estimation is taken, and the lagged term of the variable is used as its instrumental variable to circumvent the endogeneity problem, and two variables, m2 growth rate as well as policy uncertainty (epub), are introduced to replace the year effect.

Analyzing the control factors, the significant coefficients on the level of economic development (RGDP), Level of innovation (CX), the share of high energy consuming industries (GNH), and environmental regulations (HJGZ) indicate that these factors have a significant impact on the manufacturing energy growth rate. After controlling for these major factors, the speed of manufacturing catch-up and spillover effects are more pronounced when considering the national frontier. High energy consumption industry share (GNH) coefficient of -0.9006 is significant, indicating that the larger the share of high energy consumption, the slower the growth rate of energy efficiency in the manufacturing industry. It can be seen that the share of high-energy-consuming sectors is the key to improve the energy efficiency of the manufacturing industry, which is precisely one of the connotations of high-quality development of China's manufacturing industry; The level of economic development (RGDP), the level of innovation (CX), and environmental regulation (HJGZ) have a significant positive steering effect on the growth rate of manufacturing energy efficiency. In cities with a high level of economic development, industrial technology is better, and there are more funds for energy innovation and reform, which increases industrial transformation and upgrading and thus reduces energy dependence. A higher level of innovation (CX) indicates a higher level of development of new energy technologies in manufacturing, which is more favorable to energy efficiency reduction. Environmental regulations (HJGZ) can increase the cost pressure on enterprises, which forces them to adopt a more efficient use of energy. Environmental regulation can also guide enterprises to technological innovation and promote the development of clean energy and low-carbon technologies, thus improving overall energy efficiency. On the other hand, the consumption structure of coal energy is less consistent with expectations and has little impact on improving energy efficiency in the manufacturing sector, probably because the share of coal consumption in China's manufacturing energy is relatively stable.

6 Conclusions and recommendations

Based on the panel data of manufacturing industries in 30 provinces of China from 2011 to 2020, this paper adopts the non-radial directional distance function model to measure the manufacturing energy efficiency of each province in China under environmental constraints. Considering the regional imbalance in the development of China's manufacturing industry, this paper adopts the Dagum Gini coefficient method to analyze the differences in manufacturing energy efficiency among the eight regions in China. Finally, this paper constructs a catching-up model of China's manufacturing energy efficiency to analyze the absolute convergence and the conditional convergence characteristics of manufacturing energy efficiency. The main research conclusions are as follows:

1.Regarding the time axis, manufacturing energy efficiency in most provinces shows an improving trend. Overall, manufacturing energy efficiency is higher in coastal areas than inland areas. The overall Gini coefficient of energy efficiency in China's manufacturing sector shows a slight increasing trend. The primary source of the overall Gini coefficient is the hyper-variable density, accounting for basically a stable 70 percent of the total, which indicates that there is more cross-layering of manufacturing energy efficiency between regions.The second contributing factor accounts for the second largest proportion of the total is the inter-group differences, accounting for about 20 percent, mainly because of the significant differences between coastal regions and other regions.

2.Under the national efficiency frontier, China's provincial manufacturing energy efficiency catching-up effect and technology diffusion effect is significant, the level of economic development, the level of innovation, environmental regulations, and high energy consumption output value ratio has a positive impact on the growth of manufacturing energy efficiency; sub-regional manufacturing energy efficiency catching-up effect and technology diffusion effect of the significance and size of the performance of the performance of different.