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Regional differences and catch-up analysis of energy efficiency in China's manufacturing industry under environmental constraints

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Abstract
For coordinated regional growth and the development of high-quality manufacturing, China must narrow its regional energy efficiency gap and catch up inter-regionally. This paper focuses on whether China's inter-provincial manufacturing energy efficiency has technological diffusion and a catch-up effect and explores its possible influencing factors, which are important for narrowing the differences in China's manufacturing energy efficiency and promoting the improvement of the overall level of efficiency. Between 2011 and 2020, 30 Chinese manufacturing industries will be evaluated using a non-radial distance function model under environmental conditions. By employing the Dagum Gini coefficient method, regional disparities were analyzed, with hyper-variable density and efficiency discrepancies between regions making a noteworthy contribution. This paper evaluated a catch-up effect by constructing a frontier productivity model that considered the influence of China's manufacturing energy efficiency. Results show a general rise in energy efficiency, particularly in coastal regions, higher than inland ones. The Gini coefficient of energy efficiency in manufacturing experienced a slight increase; however, when comparing it to the regional efficiency frontier, the catch-up effect and technology diffusion effect of China's provincial manufacturing energy efficiency become more pronounced when taking into account the national efficiency frontier; the sub-regional manufacturing energy efficiency catch-up effect has different performances; the catch-up and technology diffusion effect is more evident after controlling for Economic development, innovation levels, the environmental regulation, and the proportion of high-energy-consumption output value and other influencing factors.

Keywords Manufacturing energy efficiency, Dagum gini coefficient, Catch-up model, The eight regions

Introduction

China has reached a late stage of industrialization, making it the world's first industrial and manufacturing nation. However, the situation of the manufacturing industry being big but not strong needs to be changed urgently. Energy consumption accounts for a high percentage of the value-added ratio, which is not in line with the level of value-added, which results in low energy efficiency. By 2021, China's manufacturing sector constituted two-thirds of the secondary sector's Emissions of greenhouse gases and energy consumption. China's "Fourteenth Five-Year Plan" plans to "deeply implement the strategy of manufacturing a strong country" and proposes to promote the high-quality development of the manufacturing industry, which clearly defines new requirements and strategic priorities for the development of China's manufacturing industry under the new stage of development. The realization of resource-saving and environmentally friendly green manufacturing is an important issue in the high-quality development of manufacturing industry. As a major energy consumer and carbon emitter, the manufacturing sector will face great challenges under the goal of "carbon peaking and carbon neutrality". "The Fourteenth Five-Year Plan calls for the proportion of manufacturing to remain stable and to avoid "premature de-industrialization". Under the clamping force of the above two objectives, improving energy efficiency in manufacturing has become an important hand in realizing the win-win situation of greening and growth of the manufacturing industry.

China's vast expanse, the regional economic development differences are large, the evolution of the law of manufacturing energy efficiency around the region also presents complexity and regional heterogeneity. If the advanced region manufacturing energy technology can effectively diffuse, backward regions of the manufacturing industry efficiency show catching up effect, will greatly improve China's overall manufacturing energy efficiency.

It is an indisputable fact that manufacturing energy efficiency differences have been observed from the results presented in the existing literature. This paper first quantitatively analyzes the evolution of regional differences in manufacturing energy efficiency and points out that the differences show a slight tendency to expand. Then we can't help but think, with the degree of marketization and the increasing liberalization of the flow of factors of production, why would it show such a result? Is there a technology diffusion effect and a technology catching-up effect between regions in China's manufacturing energy efficiency, and is there a difference in the technology diffusion and catching-up effect between regions? In this way, we try to explain the characteristic facts of the evolution of the differences in the energy efficiency of China's manufacturing industry. The possible innovations of this paper are: (1). applying the theory of appropriate technological progress to China's manufacturing sector and constructing a model of manufacturing energy efficiency catching up instead of the traditional convergence model; (2). studying for the first time the technological diffusion and technological catching up of China's manufacturing energy efficiency, which enriches the empirical evidence in this field and provides a possible explanation of the widening of the differences in the energy efficiency of the manufacturing sector. The findings of this paper also provide a policy basis for improving manufacturing energy as well as reducing regional disparities.

Literature review

Energy efficiency in China's manufacturing sector

In this paper, the evaluation method of Total Factor Energy Efficiency (TFEE) is adopted. This approach, which incorporates labor and capital into the neoclassical theory of production, addresses the limitation that the single-factor approach ignores the substitution effects between different factors of production (Yu 2021). Production frontier analysis techniques such as Data Envelopment Analysis (DEA) and Parametric Stochastic Frontier Analysis (SFA) are frequently used in existing literature to determine the total factor efficiency. In contrast to SFA, DEA does not impose specific stringent requirements on the production frontier and does not require specific assumptions on the input-output function. The analysis of this study 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-desired outputs into consideration and have widely adopted the framework of joint production. Considering the slackness of input-output variables, Tone (Tone 2001) proposed the SBM model. Fukuyama and Weber (Fukuyama and Weber 2009), on the other hand, combined the ideas of SBM and DDF to propose a non-radial, non-angular DEA method, SBM (Slack-based Measure) directional distance function. Zhou (Zhou et al. 2012) et al. (2012) pointed out that the SBM_DDF method does not formally define the function itself, and proposed the Non-Radial Distance Function (NDDF) instead of the SBM method. This method has been widely used and extended for energy efficiency measurement (Zhang et al. 2014; Zhang and Song 2020; Shi et al. 2022; Ma et al. 2023).

More and more scholars have paid attention to the energy efficiency of China's manufacturing industry. Most scholars have studied the energy efficiency of China's manufacturing industry purely from an industry perspective [9–10] or a regional perspective [11–12]. Individual scholars such as Chen (Chen et al. 2021) consider the dual perspectives of region and industry segments, and use the SBM model to measure the total factor energy efficiency of 19 manufacturing industry segments in nine provinces in China from 2001 to 2011, and discuss the differences in energy efficiency between light and heavy industries. Lin and Guan (Lin and Guan 2023) used a combination of the global DEA method and the non-radial directional distance function to measure the unified efficiency index of 28 provinces and 27 subsectors in China's manufacturing industry. As the research progresses, some scholars specialize in market reform (Zhou and Li 2021), technological progress (Chen and Liu 2021), open channels (Wei et al. 2020), infrastructure (Chen and Lin 2021), industrial integration (Dong et al. 2021) and others on energy efficiency in Chinese manufacturing industry.

Manufacturing efficiency differentials and catching up

Analyses of energy efficiency's distributional characteristics, as well as spatial variations, have been conducted in the literature, mainly through kernel density estimation [20–21], coefficient of variation (Feng et al. 2016), and Dagum Gini coefficient (Zhao et al. 2024). The main aspects of energy convergence consist primarily of σ-convergence, β-convergence test, and club convergence (Yu et al. 2018; Ouyang et al. 2021; Lv et al. 2017; He and Chen 2022). The literature on China's manufacturing industry should concentrate more heavily on regional disparities in energy efficiency. Liu (Liu 2022) evaluated and studied the evolutionary development of energy carbon emissions and their effectiveness in production, utilizing panel data from 10 sub-sectors of the industry. Scholars have yet to conduct any study of the convergence or catch-up effects of energy efficiency in manufacturing industries.

Since the 1990s, the theory of technology diffusion and interregional economic development gaps has continued to be refined. Barro and Sala-i-Martin (Barro and

Sala-i-Martin 1997) argued that technology diffusion is a key means of narrowing the productivity gap between lagging and frontier regions. Atkinson and Stiglitz (Atkinson and Stiglitz 1969) proposed the theory of appropriate technological progress, which argues that technology diffusion is not a frictionless process. Basu and Weil (Basu and Weil 1998) and Acemoglu and Zilibotti (Acemoglu and Zilibotti 2001) generalized the theory. This theory suggests that there are constraints for lagging regions to absorb technology diffusion from frontier regions. On the one hand, technological innovations in frontier regions are often developed in response to the resource endowment conditions of a particular region, and different factor endowments in different regions lead to different technological needs and different technological spillovers. On the other hand, there are differences between backward regions and frontier regions in the understanding and application of technology and the external environment, and the introduction and transformation of technology requires adaptive investment, and when the difference in factor endowment is large, adaptive investment is large and the marginal rate of return is low, which results in low incentive for investment by the government and science and technology enterprises.

Based on the above theory, the technology spillover obtained from frontier regions in different regions may have large differences, which in turn affects the catching up of manufacturing energy efficiency among regions, therefore, this paper firstly constructs a theoretical model of technology diffusion and productivity catching up in manufacturing industry based on the productivity catching up model of Bernard & Jones (Bernard and Jones 1996) and Cameron et al. (Cameron et al. 2005). Set the manufacturing production function containing three production factors, $Yit = \alpha itEPIitG(Kit, Lit, Eit)$, where Yit represents the total manufacturing output of region i in period t, Lit represents labor input, Kit represents capital input, and Eit represents energy input. $EPIit$ represents energy efficiency, αit represents the productivity of production factors other than energy, F represents the region with the highest energy production efficiency, represents the production function frontier. The growth of the level of energy efficiency in a region is influenced by two aspects: the technological spillovers from advanced regions and the impact of its own technological innovations. Referring to the models of Bernard & Jones and Cameron et al., the growth in energy efficiency is expressed as follows Eq. (1) (Bernard and Jones 1996; Cameron et al. 2005):

$$\Delta \ln EPIit = \delta \Delta \ln EPIFt + \lambda \ln \left(\frac{EPIFt - 1}{EPIit - 1} \right) + \tau Xit + uit \tag{1}$$

Where denotes the energy efficiency growth rate in province i in year t. is the growth rate of energy efficiency in the frontier region in period t, then represents the between effect of technology diffusion. represents the productivity gap between province i and the frontier region in the last period, and denotes the catch-up effect of technology diffusion. It mainly contains independent innovation.

Where $\Delta \ln EPIit$ denotes the energy efficiency growth rate in province i in year t. $\Delta \ln EPIFt$ is the growth rate of energy efficiency in the frontier region in period t, then δ represents the direct effect of technology diffusion. $\ln \left(\frac{EPI_{Ft-1}}{EPI_{it-1}} \right)$ represents the productivity gap between province i and the frontier region in the last period, and λ denotes the catch-up effect of technology diffusion. Xit mainly contains independent innovation. Subsequently this study mainly adopts this model to analyze.

This study is largely extended in the following areas: Firstly, the manufacturing energy consumption of each province is taken into account when gathering sample data, thereby avoiding industrial energy consumption as opposed to manufacturing energy consumption, as is common in other studies. Secondly, this research, for the first time, delves into the regional differences and catch-up effects of energy efficiency in China's manufacturing sector, a factor of great significance for creating high-quality policy design and evaluation. Finally, this study constructs a energy efficiency catch-up in manufacturing model for analysis, which has the advantage of showing both the technology spillover effect and the rate of productivity catch-up.

Throughout this paper, the following sections will be discussed: Part II introduces materials and techniques, Part III empirically gauges the manufacturing energy efficiency of Chinese provinces, and presents the outcomes; Part IV delves into regional disparities in manufacturing energy efficiency; In Part V, a TFP catch-up model of manufacturing energy efficiency in China is constructed; Part VI offers recommendations and conclusions.

Model establishment and data for measuring energy efficiency

Environmental production technology for manufacturing

Under the assumption of weak disposability and zero-combination of non-desired outcomes, following the analytical framework of (Fare et al. 2007), The total output value of each manufacturing industry, Y, is sought after, with capital (K), labor (L), and energy (E) co-generated in N provinces. The non-desired outputs, B, are determined by a comprehensive indicator of industrial three wastes. The following is a description of environmental production technology as shown in Eq. (2):

$$T = \{(K,\ L,\ E,\ Y,\ B):\ K,\ L,\ E\ can\ produce\ (Y,\ B)\} \tag{2}$$

Where T is to satisfy the following two axioms:

(1). $If\ (K,L,E,Y,B) \in T\ and\ 0 \leqslant \theta \leqslant 1$, them $(K,\ L,\ E, \theta Y, \theta B) \in T$ 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. Employment of the DEA technique can be utilized to construct this technology set for environmental production in the following way as shown in Eq. (3):

$$T \left\{ \begin{array}{c} ((K,L,E,Y,B): \sum\limits_{n=1}^{N} Z_n K_n \leqslant K, \sum\limits_{n=1}^{N} Z_n L_n \leqslant L, \sum\limits_{n=1}^{N} Z_n E_n \leqslant E, \\ \sum\limits_{n=1}^{N} Z_n Y_n \geqslant Y, \sum\limits_{n=1}^{N} Z_n B_n = B, n = 1...N \end{array} \right. \tag{3}$$

Non-radial direction distance function

Chung's suggestion of the directional distance function (DDF) has been utilized extensively for energy efficiency (Song and Wang 2018). This measure of efficiency can increase outputs and reduce inputs on the directional vector set by the researcher. Its desirable mathematical properties make it a radial measure with great potential for use. However, Fukuyama and Weber (Fukuyama and Weber 2009) point out that the traditional DDF may lead to overestimation of efficiency when slack variables are present. To counter this, Fei and Lin (Fei and Lin 2017) have proposed non-radial efficiency measures due to their advantages.

Zhou et al. (Zhou et al. 2012) proposed a non-radial directional distance function, which was derived from the directional distance function; we can precisely define the provincial manufacturing industry's NDDF in order to address the issue of non-zero relaxation variables as shown in Eq. (4):

$$\overrightarrow{D}(K,\ L,\ E,\ Y,\ B;\ g) = sup\{\omega^T\ \beta:\ (K,\ L,\ E,\ Y,\ B)\ +\ diag\ (\beta)\cdot g \in T\} \tag{4}$$

Where $\omega = (\omega_K\ ,\omega_L, \omega_E\ ,\omega_Y\ ,\omega_B\ )$ 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 $\beta =\ (\beta_K\ ,\beta_L,\beta_E\ ,\beta_Y\ ,\beta_B\ )\geq 0$ is the shrinkage (expansion) factor of each input-output variable, representing the non-efficiency value. Changing the proportions of inputs and outputs overcomes the radial problem with directional distance functions. Then $\overrightarrow{D}(K,\ L,\ E,\ Y,\ B:\ g)$ is the maximum shrinkable (expansion) ratio, which indicates how far the DMU deviates from the effective production boundary. Different policy objectives can generally be used to determine the directional vector.

DEA can be used to solve $\overrightarrow{D}(K,\ L,\ E,\ Y,\ B;\ g)$, whose linear programming can be written as Eq. (5):

$$\begin{aligned}
&\overrightarrow{D}(\mathrm{K},\mathrm{L},\mathrm{E},Y,\mathrm{B};g) = \max(\omega\mathrm{K}\beta\mathrm{K} + \omega\mathrm{L}\beta\mathrm{L} + \omega\mathrm{E}\beta\mathrm{E} + \omega\mathrm{Y}\beta\mathrm{Y} + \omega\mathrm{B}\beta\mathrm{B})\\
&s.t. \sum_{n=1}^{N} zn\mathrm{K}n \leq \mathrm{K} - \beta\mathrm{K}g\mathrm{K},\\
&\sum_{n=1}^{N} zn\mathrm{L}n \leq \mathrm{L} - \beta\mathrm{L}g\mathrm{L},\\
&\sum_{n=1}^{N} zn\mathrm{E}n \leq \mathrm{E} - \beta\mathrm{E}g\mathrm{E},\\
&\sum_{n=1}^{N} zn\mathrm{Y}n \geq \mathrm{Y} + \beta\mathrm{Y}g\mathrm{Y},\\
&\sum_{n=1}^{N} zn\mathrm{B}n = \mathrm{B} - \beta\mathrm{B}g\mathrm{B},\\
&zn \geq 0, n = 1, 2, \cdots N,\\
&\beta\mathrm{K},\ \beta\mathrm{L},\ \beta\mathrm{E},\ \beta\mathrm{Y},\ \beta\mathrm{B} \geq 0
\end{aligned} \tag{5}$$

Where Zn 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.

Definition of energy efficiency index under environmental constraints

To gauge the energy efficiency of the manufacturing sector in a climate-dependent environment, following (Zhang et al. 2013), 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, g is defined as $(0,\ 0,\ -E,\ Y,\ -B)$, and the weights are set as $\omega =\ (\omega_K\ ,\omega_L, \omega_E\ ,\omega_Y\ ,\omega_B)=0,\ 0,\ 1/3,\ 1/3,\ 1/3$ 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 $\beta^*{}_E, \beta^*{}_Y, \beta^*{}_B$ and define the manufacturing energy efficiency index under environmental constraints as shown in Eq. (6):

$$EEPI = \frac{1/2[(1-\beta^*{}_E)+(1-\beta^*{}_B)]}{1+\beta^*{}_Y} = \frac{1-1/2(\beta^*{}_E+\beta^*{}_B)}{1+\beta^*{}_Y} \tag{6}$$

For the sake of simplicity, the EEPI, the manufacturing energy efficiency index under environmental constraints, is hereinafter referred to as manufacturing energy efficiency.

Sample selection and grouping

In the period 2011–2021, thirty provinces, municipalities, and autonomous regions were chosen as samples due to their availability and timeliness, before a thorough examination of the energy efficiency index of China's manufacturing sector in recent years and inter-provincial comparisons.

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. The 2005 "Strategies and Policies for the Coordinated Development of Regions" divided the nation into eight economic regions, as Table 1 illustrate, which formed the basis of this paper.

Selection and description of indicators

From an input-output standpoint, the DEA-based non-radial distance function model is examined in terms of the indicators that have been more commonly employed by prior scholars, which are delineated as follows:

Input indicators

Capital investment (K): This paper, restricted to data availability, chooses the manufacturing industry's annual net fixed assets (100 million yuan) to represent the capital inputs. The perpetual inventory method, necessitating the base period of capital stock and the correct depreciation rate, is often referred to in the literature as a proxy variable. The source of data for the past years of China's Industrial Statistical Yearbook of

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 Northwest Region	Anhui, Hubei, Hunan, Jiangxi Gansu, Qinghai, Ningxia, Xinjiang
Southwest Region	Guangxi, Yunnan, Guizhou, Sichuan, Chongqing

(omitting Tibet for a total of 30 provinces) the manufacturing industry grouped by region of the leading economic indicators. Using each province's fixed asset investment price index, the data was deflated.

Labor Input (L): Industrial Statistical Yearbook of the past years, containing "Major Economic Indicators of Manufacturing Industry by Regional Grouping," the average number of workers employed annually in each province was taken into account, and it was selected as the data source for labor input.

Energy Consumption (E): This is a measure of manufacturing's energy consumption, with the unit of standard coal. This has been previously documented in the literature on the energy efficiency of the province's manufacturing sector using the gross industrial output value instead it.

This paper has conducted a comprehensive exploration of the energy consumption of the manufacturing industry, mainly due to the lack of uniformity in the statistics between provinces and cities. The following cases are addressed separately:

Firstly, manufacturing energy consumption statistics in Beijing, Shanxi, Inner Mongolia, Jiangxi, Guangdong, Guangxi, Guizhou, Yunnan, Gansu, Qinghai, Ningxia, and Xinjiang are directly available.

Secondly, the ratio of manufacturing and industrial energy consumption can be calculated based on categorized energy consumption and multiplied by the corresponding industrial energy consumption. such as Tianjin, Liaoning, Jilin, Heilongjiang, Hunan, and Shaanxi.

Thirdly, the energy consumption of above-scale manufacturing is ascertained by energy classification. One can ascertain the total energy consumption of the manufacturing industry, including Chongqing, Hebei, Fujian, Henan, and Hainan, by considering the ratio of the energy consumed in the above-scale industry to the entire industrial energy.

Fourthly, some provinces only have the total energy consumption of the manufacturing industry in some years, from which the ratio of the manufacturing industry's energy consumption to the total energy consumption of the industry in that province is first estimated, and then the energy consumption of the manufacturing industry in other years is extrapolated from it, such as 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 of different energy sources.

Expected output indicators

Manufacturing output (Y): The expected output is based on the manufacturing output of each province. 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.

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.

Measurement and analysis of energy efficiency in China's manufacturing industry

Measurement results of manufacturing energy efficiency in China's provinces

Outcomes of a technique used to evaluate the energy efficiency of 30 Chinese provinces' manufacturing industries are shown in Table 2.

As shown in Fig. 1, In terms of provinces, Beijing has been at the forefront of manufacturing energy efficiency. In addition, 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% compared with 2018. Energy consumption increased by 27% across the six major high-energy sectors from 2018 to 2019.

Regionally, the East Coastal region, with its greater overall level and more even internal development, is trailed by the South Coastal and North Coastal regions, with the South Coastal particularly advantaged by the remarkable enhancement of manufacturing energy efficiency in Guangdong and Fujian in recent years. In comparison to inland regions, coastal areas have a greater manufacturing energy efficiency. Nevertheless, it is evident that the middle and lower Yangtze River reaches have experienced a considerable rise in manufacturing energy consumption. Liaoning Province has a decline in manufacturing energy efficiency, primarily responsible for the Northeast's downturn. In the West, manufacturing is the least energy-efficient, mainly because of the abundance of energy-consuming industries, particularly in the North West.

Energy efficiency differences in China's manufacturing industry and their decomposition

Typical examples include the Thiel index and the classic Gini coefficient are regularly used to be signs of inequality. One can prevent intermingling in groups by utilizing the Dagum Gini coefficient technique to measure efficiencies disparities in total of manufacturing across China's eight economic zones, as well as regional variations, interregional disparities, and hypervariable density. According to Dagum's definition, Eq. (7) is the equation for the Gini coefficient G (Dagum 1997).

$$G = \frac{\sum_{j=1}^{k} \sum_{h=1}^{k} \sum_{i=1}^{n_j} \sum_{r=1}^{n_h} |Y_{ji} - Y_{hr}|}{2n^2 Y} \tag{7}$$

The number of economic zones eight is denoted by k, with j and h subscripts representing them; i and r are subscripts of provinces. The number of provinces within economic

Table 2 Manufacturing energy efficiency in 30 provinces of China under environmental constraints

Region	Province	2011	2012	2013	2014	2015	2016	2017	2018	2019	2020	Average Value
North Coastal Region	Beijing	0.417	0.454	0.607	0.683	0.707	0.83	0.854	0.89	0.961	1	0.74
	Tianjing	0.219	0.238	0.26	0.309	0.356	0.384	0.245	0.245	0.249	0.267	0.277
	Hebei	0.128	0.172	0.177	0.222	0.257	0.286	0.175	0.12	0.142	0.156	0.183
	Shandong	0.23	0.267	0.294	0.346	0.357	0.368	0.322	0.197	0.172	0.178	0.273
East Coast Region	Shanghai	0.399	0.414	0.423	0.449	0.452	0.465	0.51	0.531	0.54	0.56	0.474
	Jiangsu	0.423	0.473	0.538	0.517	0.617	0.66	0.605	0.514	0.465	0.505	0.537
	Zhejiang	0.433	0.426	0.45	0.466	0.462	0.482	0.443	0.453	0.466	0.503	0.458
South Coastal Region	Fujian	0.289	0.293	0.323	0.34	0.372	0.395	0.434	0.47	0.522	0.496	0.393
	Guangdong	0.332	0.338	0.386	0.429	0.452	0.5	1	0.749	0.917	1	0.61
	Hainan	0.207	0.207	0.218	0.256	0.273	0.144	0.137	0.161	0.165	0.165	0.193
Northeast Region	Liaoning	0.353	0.382	0.37	0.441	0.332	0.147	0.147	0.112	0.179	0.144	0.216
	Jilin	0.231	0.291	0.334	0.473	0.61	0.42	0.359	0.229	0.296	0.303	0.354
	Heilongjiang	0.095	0.105	0.128	0.148	0.201	0.206	0.111	0.116	0.151	0.173	0.143
Middle reaches of the Yellow River Region	Shannxi	0.05	0.11	0.127	0.132	0.129	0.13	0.09	0.068	0.161	0.099	0.11
	Inner Mongolia	0.127	0.135	0.14	0.148	0.143	0.139	0.071	0.064	0.073	0.071	0.111
	Henan	0.171	0.191	0.226	0.285	0.366	0.419	0.048	0.269	0.28	0.267	0.287
	Shanxi	0.171	0.178	0.23	0.377	0.449	0.387	0.431	0.266	0.32	0.27	0.308
Middle reaches of the Yangtze River Region	Anhui	0.248	0.272	0.331	0.374	O.424	0.469	0.438	0.372	0.357	0.337	0.362
	Jiangxi	0.239	0.282	0.342	0.379	0.413	0.461	0.425	0.398	0.43	0.44	0.381
	Hubei	0.214	0.221	0.33	o.344	0.386	0.416	0.429	0.456	0.492	0.443	0.373
	Hunan	0.227	0.222	0.293	0.302	0.334	0.411	0.354	0.26	0.284	0.301	0.299
Northwest Region	Gansu	0.163	0.181	0.2	0.222	0.249	0.225	0.205	0.156	0.147	0.155	0.19
	Qinghai	0.066	0.064	0.067	0.073	0.076	0.083	0.062	0.065	0.067	0.076	0.07
	Ningxia	0.072	0.08	0.089	0.09	0.086	0.09	0.073	0.075	0.064	0.061	0.078
	xinjiang	0.107	0.105	0.095	0.097	0.104	0.106	0.1	0.072	0.091	0.099	0.097
Southwest Region	Guangxi	0.125	0.146	0.158	0.175	0.187	0.212	0.205	0.145	0.137	0.129	0.162
	Chongqing	0.149	0.158	0.256	0.257	0.29	0.352	0.331	0.297	0.322	0.33	0.274
	Sichuan	0.133	0.135	0.153	0.177	0.189	0.235	0.235	0.225	0.224	0.236	0.195
	Guizhou	0.083	0.127	0.143	0.092	0.138	0.247	0.145	0.076	0.123	0.128	0.124
	Yunnan	0.064	0.134	0.166	0.101	0.109	0.18	0.122	0.038	0.241	0.218	0.139
							0.196					

zone j(h) is denoted by $n_j\,(n_h)$, the manufacturing energy efficiency of province i(r) within economic zone j(h) is represented by $Y_{ji}\,(Y_{hr})$, and all provinces are represented by n. Before the decomposition, the eight energy efficiency averages of the eight economic zones were ranked as $Y_{j1} \leqslant Y_{j2} \leqslant Y_{j3} \leqslant \cdots \leqslant Y_{j8}$ first.

Then, three components make up the Gini coefficient: intra-region variation contribution$(G\omega)$, inter-region variation contribution (G_{nb}), and hyper-variable density contribution (G_t), which satisfy the relationship Equation $G\ = G_{\ \omega}\ + G_{\ nb} + G_{\ t}$.

According to Table 3, manufacturing energy efficiency has improved in eight major Chinese regions between 2011 and 2020. The country's total Gini coefficient shows a fluctuating and slightly increasing trend. The stark contrast divergence in energy efficiency between the North Coastal and Middle Yellow River regions in the manufacturing sector industry is evident, with the latter's growth being the latter exhibiting more balanced even growth. Conversely, East Coastal and Middle Yangtze River regions have fewer intra-regional disparities and more balanced inter-regional growth.

The primary source of the overall Gini coefficient is hyper-variable density, as seen quite intuitively in Fig. 2. In spite of recent declines, hyper-variable density remains stable at 70%, indicating cross-layering of manufacturing energy efficiency. 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%, with a slight decrease in recent years. Intra-regional variations contribute the least, with a slight tendency to increase but remaining stable at around 7% in recent years.

Due to space constraints Fig. 3 only shows the average difference between the three major coastal regions and the other regions from 2011 to 2020, as well as the average rate of change. The average rate of change is positive for all regions except for the east coast, the middle reaches of the Yangtze River, and the southwest, indicating that the differences between the coastal regions and the other regions are widening, with the northern coastal region having a larger difference with the other regions.

Catch-up analysis of energy efficiency in China's manufacturing industry

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

With the Gini coefficient of energy efficiency growing slowly and the gap between regions increasing, is there any impact of technology diffusion from frontier regions and catching up from lagging regions? Does appropriate technological progress apply to the energy efficiency aspect of manufacturing in China, i.e., does the process of technology diffusion and catch-up show regional differentiation? In order to characterize this process, Bernard and Jones' TFP catch-up model is the main topic of this paper, which examines the convergence of energy efficiency in China's provincial manufacturing sector (Bernard and Jones 1996).

Construct the following productivity catch-up model as described earlier, as shown in Eq. (8):

$$\Delta lnEEPI_{it} = \delta\Delta lnEEPI_{Ft} + \lambda ln(\frac{EEPI_{\mathrm{Ft}} - 1}{EEPI_{it}}) + \pi X_{it} + u_{it} \tag{8}$$

In this model, $\Delta lnEEPI_{it}$ is the manufacturing energy efficiency growth rate of province i in year t. $\Delta lnEEPI_{Ft}$ denotes the movement of the energy efficiency frontier in

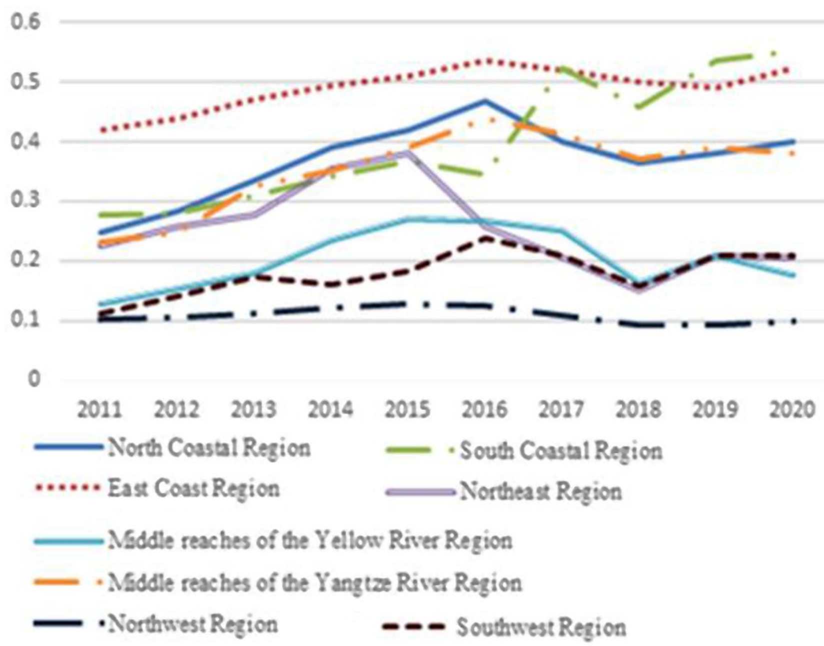

Fig. 1 Trends in manufacturing energy efficiency in eight regions, 2011–2020

Table 3 Manufacturing energy efficiency in 30 provinces of China under environmental constraints

Year	Overall Differences	Intra-regional variations							
	Nationwide	North Coastal	East Coastal	South Coastal	North-east Coastal	Middle reaches of the Yellow River	Middle reaches of the Yangtze River	North-west Region	South-west Region
2011	0.306	0.221	0.018	0.100	0.253	0.197	0.030	0.200	0.159
2012	0.279	0.193	0.030	0.105	0.238	0.116	0.059	0.219	0.042
2013	0.280	0.248	0.055	0.121	0.194	0.136	0.029	0.224	0.109
2014	0.295	0.228	0.054	0.112	0.204	0.232	0.047	0.236	0.236
2015	0.288	0.201	0.072	0.109	0.239	0.272	0.047	0.260	0.181
2016	0.293	0.221	0.081	0.228	0.236	0.259	0.031	0.219	0.031
2017	0.371	0.331	0.069	0.366	0.267	0.349	0.039	0.259	0.196
2018	0.409	0.406	0.034	0.284	0.170	0.303	0.103	0.188	0.340
2019	0.375	0.416	0.034	0.312	0.154	0.259	0.111	0.183	0.192
2020	0.388	0.410	0.025	0.335	0.172	0.270	0.087	0.195	0.196
Average Value	0.3284	0.2875	0.0472	0.2072	0.2127	0.2393	0.0583	0.2183	0.1682

period t (which can be regarded as technological progress) and $\frac{ln\ EEPT_{Ft}-1}{EEPI_{it}-1}$ represents the gap between the manufacturing energy efficiency of the province i and the frontier in period t-1, which can be described as Gapit-1, with the more significant value indicating the more significant gap between the energy efficiency and the production frontier in the province. X_{it} indicates other important factors affecting the rate of efficiency growth, such as autonomous innovation.

From this model (8) can be expressed as shown in Eq. (9):

$$\Delta lnEEPI_{it} = \alpha_2 \Delta lnEEPI_{Ft} + \lambda G_{apit-1} + \tau X_{it} + u_{it} \tag{9}$$

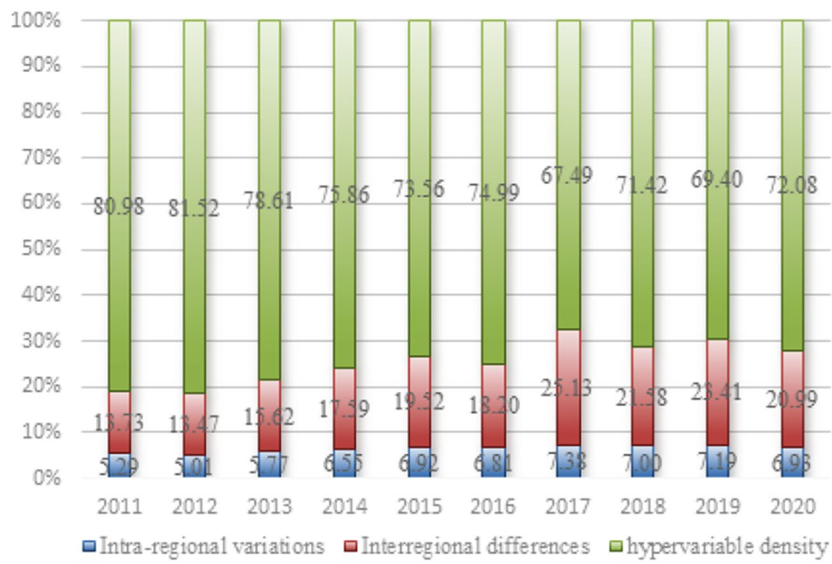

Fig. 2 Spatial Gini coefficient decomposition for eight regions

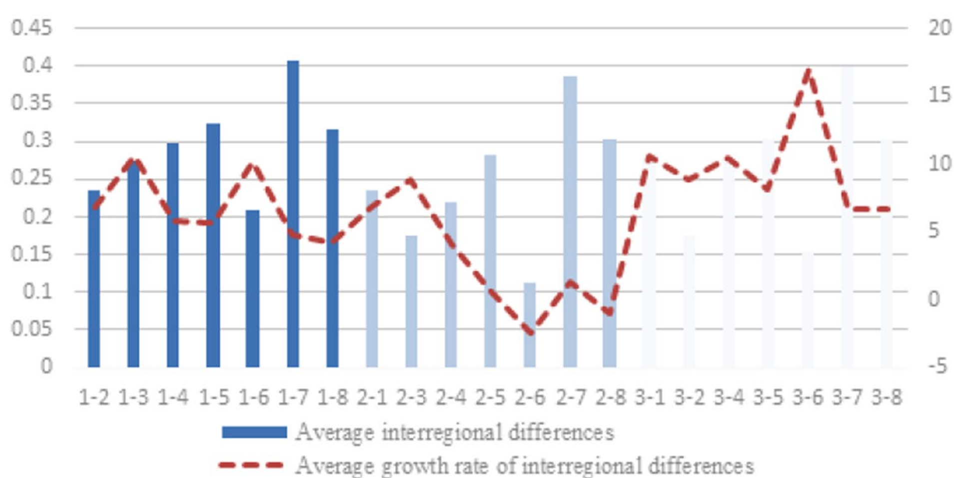

Fig. 3 Average difference between the three coastal regions and the rest and their average growth rates (%)

This paper concentrates on λ and α2. The coefficient λ denotes the catch-up consequence of technology diffusion. If $\lambda > 0$, it shows that the energy efficiency of the manufacturing sector in the preceding period was lower and the gap between it and the production boundary was larger, then the sample's energy efficiency will increase more rapidly in the present period. α2 measures the efficiency frontier's pull on the other provinces' energy growth rate, which can be considered a direct effect of technology diffusion. Both $\triangle lnEPI_{it}$ and Ga_{pit-1} contain EPI_{it-1}, so the two have a direct bi-directional causal relationship. Thus, there is an endogeneity problem with t explanatory variable Gapit−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. By avoiding joint causality, the variable's lagged term guarantees that the instrumental variable is reasonable.

Table 4 Manufacturing Energy efficiency productivity catch-up model

Dependent variable: growth rate of energy efficiency in manufacturing	GMM-robust (1)	(2)	(3)	(4)
Energy efficiency gap (GAP)	0.5413*** (0.171)	0.4699 ***(0.162)	——	——
Efficiency Frontier Growth Rate (mg)	0.8368*** (0.224)	0.5846*** (0.221)	——	0.4399*** (0.128)
Regional frontier energy efficiency gaps (GAPR)	——	0.1137 (0.1223)	0.4344*** (0.144)	——
growth rate (mgr)	——	0.4111 (0.104)	0.5973*** (0.1236)	——
GAP2	——	——	——	0.3066** (0.162)
GAP3	——	——	——	0.5069*** (0.202)
GAP4	——	——	——	0.5765*** (0.199)
GAP5				0.6317*** (0.200)
m2	0.0601*** (0.009)	0.04585*** (0.0105)	0.0392*** (0.009)	0.0469*** (0.011)
epu	-0.0045 (0.012)	-0.0068 (0.0101)	0.0109 (0.0073)	0.0280*** (0.010)
Province effect	Y	Y	Y	Y
Observations	240	240	240	240
Number of dmu	30	30	30	30
Kleibergen-Paap rk LM statistic	17.179	15.059	17.588	——
P-value	0.000	0.000	0.000	——
Kleibergen-Paap rk Wald F statistic	17.344	5.816	15.821	——
Stock-Yogo weak ID test critical values: 10R-squared	0.3721	0.4464	0.3824	0.2658

(Kleibergen-Paap rk LM statistic reports the results of the unidentifiable test, with p-values of 0 all rejecting the original hypothesis of unidentifiable; Kleibergen-Paap rk Wald F statistic reports the results of the test of the weak instrumental variable, with a critical value of greater than 10% indicating that the instrumental variable can be considered to be qualified)

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 catchingup impact on the efficiency frontier is substantial and the provincial manufacturing energy efficiency has absolute convergence characteristics. This conclusion is consistent with that of the absolute convergence characterizing Chinese industry as presented in the current literature, except that this paper employs a catch-up model that can show both the direct and catch-up effects of technology diffusion.

In the second and third columns, following the method of introducing multiple frontiers (Gong 2022), this paper presents the regional frontier. The results in column 2 show 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 indicates that the diffusion and catch-up of energy technologies in manufacturing is not affected by geographical distance. It is also an important finding of this paper that, unlike other industries, such as agriculture where technology diffusion is strongly influenced by geographic distance, the diffusion of energy technologies in manufacturing is rarely influenced by geographic distance. Consequently, only the national frontier will be employed in the subsequent studies.

In Column 4, discarding the GAP variable, the energy efficiency of manufacturing industries in each province of the nation is divided into five levels instead. 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.

Convergence model of manufacturing energy efficiency in eight regions of China

In order to explore whether China's manufacturing energy efficiency applies to the theory of appropriate technological progress, i.e., whether there are differences in technological diffusion and catching up among regions with different resource endowments, this paper constructs a productivity catching-up model for the eight regions in China for analysis using the national efficiency frontier. From the results in Table 5, absolute convergence characteristics of manufacturing energy efficiency are inconsistent across regions. Specifically, manufacturing energy catch-up efficiency and frontier technology diffusion effects are notable in the middle reaches of the Yellow River and Yangtze River. 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.

A model of energy efficiency catch-up in China's manufacturing industry with the addition of control factors

In order to analyze other factors affecting the growth of manufacturing energy efficiency in the provinces, factors that may affect manufacturing energy efficiency at the provincial level are considered to be introduced as control variables Xit in the above model, as shown in Eq. (10).

$$\triangle\, lnEEPI_{it} = \delta \Delta lnEEPI_{Ft} + \lambda ln(\frac{EEPI_{F\mathrm{t}} - 1}{EEPI_{it}}) + \pi X_{it} + u_{it} \tag{10}$$

This paper considers both endogenous and external factors. With regard to endogenous factors, the industry's own technological innovation and energy management experience will improve energy efficiency. The following factors are considered in this part: the degree of independent innovation, which has been described in the previous section. The level of economic development, in areas with a higher level of economic development, enterprises have more capital and resources to invest in technological innovation and energy management, thus improving energy efficiency; the degree of openness, in areas with a higher degree of openness to the outside world, it is easier for manufacturing enterprises to come into contact with the international advanced technology and

Table 5 Comparison of efficiency productivity catch-up models for eight regions

Dependent variable: growth rate of energy efficiency in manufacturing	GMM-robust Nationwide	North Coastal	East Coastal	South Coastal	Northeast reaches of region	Middle reaches of the Yellow River	Middle reaches of the Yangtze River	Northwest Region	South-west Region
Energy efficiency gap (GAP)	5413*** (0.171)	2772*** (0.118)	0.3833 (0.301)	0.2136 (0.186)	0.5050** (0.296)	0.3789** (0.210)	0.5417*** (0.262)	0.4123** (0.2123)	0.4209 (1.741)
Efficiency Frontier Growth Rate(mg)	0.8368*** (0.224)	0.3556 (0.340)	0.3725 (0.271)	0.4557 (0.467)	0.4338(463)	0.8945*** (0.431)	0.7394*** (0.231)	0.3775 (0.3170)	1.5910 (1.072)
M2 growth rate	0.0601*** (0.009)	0.0707*** (0.020)	0.0278*** (0.012)	0.0172 (0.028)	0.0981*** (0.039)	0.0658*** (0.028)	0.0407*** (0.008)	0.0536***(0.013)	0.1309** (0.071)
Policy uncertainties (epu)	-0.0045 (0.012)	0.0012 (0.0150)	−0.0102 (0.01389)	−0.0129 (0.0157)	−0.0124 (0.035)	−0.0034 0.029	−0.0132 (0.0129)	-0.0444 (0.66)	0.5116 (0.549)
Province effect	Y	Y	Y	Y	Y	Y	Y	Y	Y
Observation	240	32	24	24	24	32	32	32	32
Number of dmu	30	4	3	3	3	4	4	4	4
Kleibergen-Paap rk LM statistic	17.179	6.580	5.958	9.285	10.974	9.184	4.539	4.861	4.910
P-value	0.000	0.0103	0.0147	0.0023	0.001	0.002	0.0331	0.0275	0.024
Kleibergen-Paap rk Wald F statistic	17.344	30.916	16.38	18.467	26.905	20.122	11.249	9.093	9.011
Stock-Yogo weak ID test critical values	8.96	8.96	8.96	8.96	8.96	8.96	8.96	8.96	8.96
R-squared	0.3721	0.4538	0.1946	0.3442	0.3442	0.4189	0.6801	0.4253	0.2504

*** p¡0.01, ** p¡0.05, * p¡0.1

(Kleibergen-Paap rk LM statistic reports the results of the unidentifiable test, with p-values of 0, all rejecting the original hypothesis of unidentifiable. The Kleibergen-Paap rk Wald F statistic reveals the assessment findings of the feeble instrumental variable, with a critical value of more than 10%, implying that the instrumental variable is qualified.)

management experience, thus improving energy efficiency; external factors are mainly considered in terms of changes in the structure of manufacturing industries, environmental regulations, energy consumption structure and other factors. In terms of external factors, the main consideration is the change of industrial structure of manufacturing industry, environmental regulation, energy consumption structure and other factors. The more advanced the industrial structure of the manufacturing industry, the higher the proportion of high-tech industries, the higher the energy efficiency; the larger the proportion of high-energy-consuming industries, the lower the energy efficiency of the manufacturing industry; from the perspective of the energy consumption structure, the higher the proportion of the use of clean energy, the higher the efficiency of the use of energy; environmental regulation can prompt enterprises to optimize the structure of energy consumption, and to guide the enterprise to carry out technological innovation to promote the development of clean energy and low-carbon technology, thus improving the overall energy efficiency. Environmental regulation can initially optimize the energy consumption structure of enterprises, and guide them to carry out technological innovation, promote the development of clean energy and low-carbon technologies, and thus improve the overall energy utilization efficiency.

(1) To measure the degree of technological innovation, the percentage of R&D outlay to regional GDP in each province is employed.

(2) GDP per capita is the measure of economic development in each province.

(3) To gauge the openness of each province, the ratio of foreign capital usage to GDP is employed.

(4) The level of advanced manufacturing industry structure. Following the example of (Fu et al. 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 demonstrates the heightened industrial structure of each province's manufacturing industry.

(5) The percentage of energy-intensive manufacturing industries is expressed as the ratio of the six most energy-demanding manufacturing industries' production to that of each province's manufacturing industry.

(6) To determine energy consumption structure, the ratio of coal utilization to the total energy consumed in each province is utilized.

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

Employing GMM-robust estimation, the instrumental variable is the lagged term of the variable, thereby avoiding the endogeneity issue, similar to the preceding section. M2 growth rate and policy uncertainty (epub) are introduced to replace the year effect.

In Table 6, with control factors added to the manufacturing above energy efficiency catch-up model. Compared with the first column, the increase in the coefficient of manufacturing efficiency frontier growth rate (mg) in the second column indicates that the positive spillover effect of the manufacturing energy frontier increases after controlling for relevant conditional factors. The manufacturing energy efficiency gap (GAP) coefficient becomes larger, indicating that China's provincial manufacturing energy efficiency catch-up effect has accelerated. This finding is broadly similar to that of the study of industrial energy efficiency in China, where the conditional convergence characteristics

Table 6 The catch-up model of energy efficiency in manufacturing with the addition of control variables

Dependent variable: growth rate of energy efficiency in manufacturing	GMM-robust (1)	(2)
Energy efficiency gap (GAP)	0.5413*** (0.171)	0.9103*** (0.2425)
Efficiency Frontier Growth Rate (mg)	0.8368*** (0.224)	1.0796*** (0.3021)
Regional frontier energy efficiency gaps (GAPR)		
efficiency frontier growth rate (mgr)		
Level of economic development (RGDP)		1.0557*** (0.3911)
Openness level (KF)		-0.4380 (2.33)
Innovation level (CX)		0.0879*** (0.059)
High-end industrial structure (CYGJH)		0.0014 (0.032)
Percentage of energy-intensive industries (GNH)		-0.9006*** (0.5291)
Environmental regulation (HJGZ)		14.808*** (5.341)
Energy consumption structure (XFJG)		0.9326 (0.572)
Year (EPU, M2)	Y	Y
Province effect	Y	Y
Observations	240	240
Number of dmu	30	30
Kleibergen-Paap rk LM statistic	17.179	10.220
P-value	0.000	0.000
Kleibergen-Paap rk Wald F statistic	17.344	9.698
Stock-Yogo weak ID test critical values	8.96	8.96
R-squared	0.3721	0.4402

*** p¡0.01, ** p¡0.05, * p¡0.1

(Kleibergen-Paap rk LM statistic reports the results of the unidentifiable test, with p- values of 0 all rejecting the original hypothesis of unidentifiable; Kleibergen-Paap rk Wald F statistic reports the results of the test of the weak instrumental variable, with a critical value of greater than 10% indicating that the instrumental variable can be considered to be qualified)

of the Chinese manufacturing sector are enhanced after controlling for a number of other factors.

Analyzing the results from the control factors, the significant coefficients of the level of economic development (RGDP), the level of innovation (CX), and environmental regulation (HJGZ) indicate that these factors have a significant positive effect on the growth rate of manufacturing energy. The share of high energy consuming industries (GNH), on the other hand, shows a significant negative effect. These are consistent with the setting of theoretical expectations.

In stark contrast, the coal energy consumed is not in accordance with expectations and has had minimal impact on improving energy efficiency in the manufacturing sector, probably because coal consumption in China's manufacturing energy is consistent.

Conclusions and recommendations

This paper adopts the NDDF model to measure the manufacturing energy efficiency of each province in China under environmental constraints by utilizing panel data from 30 provinces between 2011 and 2020. Employing the Dagum Gini coefficient technique, this paper examines the disparities between eight Chinese regions in the Manufacturing energy efficiency sector. Constructing a catch-up model of China's manufacturing energy efficiency, this paper assesses the catch-up effect and technology diffusion effect of China's manufacturing energy industry. The main research conclusions are as follows:

(1). The Gini coefficient of energy efficiency in China's manufacturing sector, when taken into account over the time axis, reveals a slight rise. In most provinces, this trend is further enhanced by the higher levels of energy efficiency found in coastal areas compared to inland areas. The primary source of the overall Gini coefficient is the hypervariable density, accounting for basically a stable 70% of the total, indicating 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%, mainly because of the significant differences between coastal regions and other regions.

(2). There are technology diffusion and catch-up effects in manufacturing energy efficiency between provinces in China. At the same time, technology diffusion and catching-up effects are not significantly affected by geographical distance. There are differences in technology diffusion and catching-up effects in manufacturing industries in different regions. The growth of manufacturing energy efficiency is significantly affected by economic level, innovation level, environmental regulation and high energy consumption ratio.

Using the findings of this paper as a basis for policy recommendations, we suggest the following.

(1) Differentiated development policies have been formulated based on each region's characteristics. First of all, the northern coastal, southern coastal and eastern coastal economic zones and other efficiency frontier regions should actively promote industrial low-carbon scientific and technological innovation, build up the key technological support for the improvement of energy efficiency in the manufacturing industry, and give full play to the demonstration effect and radiation-driven role. Secondly, non-efficiency frontier regions, especially low-efficiency regions with insignificant technology diffusion and catching-up effects, such as the north coast, the northeast region, the northwest region, etc., should continue to break through the mechanism, system and market barriers, optimize their own industrial structure, weaken the gap between resource endowment and institutional environment with the frontier regions, promote the flow and exchange of talents, capital and technology between the frontier regions, and combine with their own characteristics to carry out appropriate technological transformation and innovation, as well as to improve the energy-efficiency of the manufacturing industry. Combined with its own characteristics, it will carry out appropriate technological transformation and introduction, promote the diffusion of technology from the efficiency frontier regions, and improve the speed of catching up with the energy efficiency of its manufacturing industry.
(2) In order to reduce the differences in energy efficiency of manufacturing industries in different regions and improve energy efficiency, we can start from the following aspects: first, gradually reduce the proportion of high-energy-consuming industries, cultivate strategic emerging industries based on green technology, and promote the optimization and upgrading of industrial structure; second, continuously encourage manufacturing enterprises to increase scientific and technological innovation, optimize

the process, and promote the innovation and development of new energy-saving technologies; third, implement appropriate environmental regulations. Differentiated environmental regulation policies should be formulated according to the pollution intensity of the manufacturing industry and different industries in different regions, and a regional environmental supervision and coordination mechanism should be established to clarify the objectives, tasks and responsibility system, and to increase the implementation efforts to avoid the pollution transfer effect.

(3) Specifically, Efficiency frontiers such as the North Coast, South Coast and East Coast Economic Zones should strengthen their energy technology upgrading efforts and improve their energy management experience. For example, governments should adopt subsidy policies or increase environmental regulations to promote the development of energy technology trading markets. The Great Northwest Economic Region should eliminate backward production capacity as soon as possible, reduce the proportion of high-energy-consuming industries and promote the transformation of traditional high-energy-consuming industries. At the same time, it should better develop emerging green industries and promote the deep integration of emerging green industries with traditional high-energy-consuming industries; the Northeast Economic Zone should continue to strengthen the policy support for "revitalizing the old industrial bases in the Northeast", focusing on the green and low-carbon development of the industrial sector, and promoting the green and low-carbon transformation of the traditional industries; and the economic zones of the Southwest, the Yellow River, and the middle reaches of the Yangtze River should continue to strengthen the policy support for "promoting the rise of central China". The economic zones of Southwest China, the Yellow River and the middle reaches of the Yangtze River should continue to strengthen the policy support of "Promoting the Rise of Central China", eliminating the backward production capacity and cultivating the characteristic emerging industries, for example, the middle reaches of the Yellow River should further improve the development mode of the industrial chain of the coal chemical industry, and promote the development of the coal chemical industry in a high-end, diversified and low-carbon way.

The research in this paper still has many shortcomings, first of all, it mainly uses inter-provincial data and cannot find out the specific mechanisms and causes of technology diffusion and catching up at the firm level, which needs to be analyzed from a more microscopic point of view in the subsequent research. Secondly, this paper has not yet carried out in-depth analysis of the actual situation of each region, in terms of regional resource endowment, industrial structure and other specific aspects of the analysis. Finally, the energy efficiency differences in China's manufacturing industry still need to be tracked and quantified by further expanding the sample.

Author contributions

W.C. contributed to Writing - Original Draft; X.W. contributed to Funding acquisition and Writing - Review & Editing.

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Data availability

No datasets were generated or analysed during the current study.

Declarations

Ethical approval
Not applicable.

Consent to participate
Not applicable.

Consent for publication
Not applicable.

Competing interests
The authors declare no competing interests.

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