

# Research Article

# Research on Industry Difference and Convergence of Green Innovation Efficiency of Manufacturing Industry in China Based on Super-SBM and Convergence Models

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Received 15 August 2021; Revised 28 October 2021; Accepted 6 November 2021; Published 26 November 2021

Academic Editor: Yiwen Zhang

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To accurately grasp the current situation of green innovation efficiency in the manufacturing industry in China, this paper analyzes the differences and convergence characteristics of green innovation efficiency in various industries. Based on the panel data of 29 manufacturing industries in China from 2010 to 2019, the super-slack-based measure (Super-SBM) model measures the green innovation efficiency of manufacturing industries whose evolution characteristics are classified and analyzed from the perspective of technical demand. The Dagum Gini coefficient decomposition method indicates the source of industry differences in green innovation efficiency of the manufacturing industry in China with its convergence characteristics analyzed from the time dimension by constructing  $\sigma$  and  $\beta$  convergence models. The results reveal the improvement of green innovation efficiency of the Chinese manufacturing industry with obvious distinctions among different sectors and the industries with high green innovation efficiency, mostly high-end technology ones. The narrowing overall difference of green innovation efficiency in the manufacturing industry is accompanied by the lowest contribution rate of super-variable density, with the disparities between groups being the main source. It also shows the fluctuation of the intermittent  $\sigma$  convergence characteristics of the national manufacturing industry as a whole and low-end and high-end technology industry groups. However, the entire manufacturing industry and the three groups witness the absolute  $\beta$  convergence trend, with an ununiform convergence rate. The research will provide a reference for further upgrading the efficiency of green innovation in the industry and help to achieve the goals of carbon emission reduction and neutrality with the policy implications for promoting high-quality development of the manufacturing industry.

# 1. Introduction

With the transformation from high-speed growth to highquality growth economic in China, the manufacturing industry, as the main body of the national economy, has developed extensively with high pollution and energy consumption. In responding to the global environmental governance and green economic development, a highquality development goal will be obtained with refined independent innovation capability and cutting-edge core technologies. As a major manufacturing country globally, China sees its manufacturing industry as the big energy consumer and carbon emitter, with the industry being the key for its national energy-saving goal [1]. Under the 2030 carbon peak target and the 2060 carbon-neutral vision, pollution, carbon reduction, and green innovation will abound in the high-quality development of the Chinese manufacturing industry. Recently, major manufacturing countries have intensified their scientific and technological innovation, actively promoting green creation in manufacturing. Despite some world-leading innovative industries and technologies, China still undergoes an unbalanced innovation development with resource and environmental dilemmas in most cases [2]. To achieve a high-quality manufacturing industry, it is necessary to take green transformation as the development goal, innovation and development as the core driving force, green development and innovation drive as the combination point. Also, it is necessary to promote the two-way balance between economic growth and resources and environment to further enhance its green innovation efficiency [3].

Green innovation sustains environmental, ecological, and sustainable innovations. The green manufacturing industry should anchor its development goal, comprehensively grasp the products, processes, technologies, services, and the management of the whole life cycle to realize multidimensional and whole processes to reduce the environmental pressure caused by the manufacturing industry [4]. Therefore, it is important to promote various industries to achieve carbon neutrality by studying the green innovation efficiency of the manufacturing industries and giving some suggestions to different sectors for efficiency improvement [5].

Since the concept of sustainable development made its debut, green innovation has caught much attention of the researchers worldwide. They have done a lot of research on it from different perspectives and yielded fruitful results. Scholars analyzing the green innovation efficiency from regional heterogeneity believe that the efficiency of green innovation in China has increased [6], with a low-efficiency level overall [7]. The absolute and conditional  $\beta$ -space convergences characterize the great spatial differences in the green innovation efficiency among the provinces. Under different production technology conditions, the efficiency of regional green innovation in China decreased from east to west to center [8]. However, some scholars believe that the national green innovation efficiency shows a step-like decline in the eastern, the central, and the western regions, with the gap in green innovation efficiency among the regions narrowed by the reasonable flow of factors, optimized allocation of innovation resources, and stimulated innovation vitality [9]. In addition, scholars who studied the green innovation convergence have indicated the significant trend of absolute and conditional  $\beta$  convergences in the regional green innovation efficiency across the board [9, 10]. However, after studying the rural green efficiency development, the scholars unveiled the gradually enhanced efficiency of rural green development without an absolute  $\beta$  convergence and "catch-up effect" between the regions [11].

By studying the industrial green innovation efficiency, the scholars discovered innovative and unsustainable phenomena in the heavily polluting industries in China, with green efficiency being the key to lowering the overall green innovation efficiency of the industry. Heavy-polluting industries need to strictly implement the environmental regulation policies, increase green technology development and application, and promote green transformation [12, 13]. There are significant distinctions in green innovation efficiency among different pollution-intensive industries. According to the actual development needs, all industries should follow green development and innovation and promote industrial agglomeration innovation and green transformation [14]. The Chinese manufacturing industry shifts toward green innovation with room for green innovation efficiency improvement, but there are significant differences in the east and west, and the regional differences are gradually expanding [15]. The lower green innovation efficiency of all industries than that of the whole

manufacturing industry is followed by the higher efficiency of the patent-intensive manufacturing industry than that of nonpatent-intensive counterparts because of industrial heterogeneity [14, 16]. With the increasing implementation effect of favorable policies, China's manufacturing industry has realized the dual-path transformation of emission reduction and efficiency increase [17]. The green innovation efficiency of manufacturing industry in the Yangtze River Economic Belt has been steadily improved. However, there is still a large space for improvement [18]. Some scholars divide the efficiency of green innovation into two stages: research and development (R&D) and achievement transformation, as well as the measurement of the regional efficiency of the high tech manufacturing industry [19]. Luo et al. maintained the disparate green technology innovation efficiency in industries despite the annual swelling in the national green innovation efficiency of the strategic new ones [20]. Li et al. believed that the green innovation efficiency of the Chinese high tech industries evolved from the large differences in low efficiency to high efficiency, with the climbing proportion of high-efficiency provinces [21]. Claudio et al. measured the technological innovation efficiency of the Spanish manufacturing industry from 1992 to 2005 and found big industry differences in the technological innovation efficiency [22].

The summary of the worldwide factors affecting the manufacturing efficiency of green innovation unveiled the different influences of R&D investment, government support, environmental regulation, and enterprise scale. Yi et al. believed that the government R&D subsidies and ecological regulations improved the manufacturing green innovation efficiency in the manufacturing industry [23], with the firm size and industrial structure impeding the green innovation efficiency that is irrelevant to economic openness. Nuryakin et al. exploited the Batik industry in Indonesia to test the factors of green product and green process innovations of Batik enterprises [24]. Based on the relevant data of the development of the German manufacturing industry, Nuryakin et al. adopted the bivariate Probit model to study the factors affecting its green innovation and believed that increasing R&D investment and environmental regulation could promote green innovation [25].

The existing research mainly focuses on three aspects: regional green innovation efficiency [26], industrial green innovation efficiency [27], and the factors of green innovation efficiency [28]. Insufficient research on the difference and convergence of manufacturing green innovation efficiency from the heterogeneity of industry technology demand is accompanied by the universally proposed policy suggestions and promotion paths void of industry pertinence. Therefore, it is of theoretical and practical significance to accurately grasp the green innovation efficiency of the manufacturing industry with differentiation measures to promote the manufacturing industry, coordinated development of innovation and resources, and the environment.

This paper ingeniously divided the 29 domestic manufacturing industries into high-end, middle-end, and low-end technology industries concerning different technical requirements. The measurement of green innovation efficiency of the manufacturing industry from 2010 to 2019 was followed by the obtained sources of differences in that of various sectors with the convergence trend study of industry differences based on *s* and  $\beta$  convergences. To narrow the industry differences and improve the efficiency of green innovation in the Chinese manufacturing industry, this paper finally puts forward some countermeasures for green innovations and the environment.

The remainder of the paper is organized as follows: section 2: the model detailing, section 3: data presenting, section 4: the empirical result discussing, and section 5: conclusion with policy implications.

#### 2. Methodology and Models Specification

2.1. Super-SBM Model. The super-slack-based measure (Super-SBM) model is a nonradial and nonangle efficiency evaluation model proposed by Tone [29]. Compared with the traditional CCR and BCC models, this one overcomes the relaxation effect of elements, considers the relaxation variables in the objective function, and solves the scheduling problem when the SBM model cannot simultaneously distinguish multiple effective decision-making units. Therefore, the super-SBM model with an undesired output for the green innovation efficiency measurement of the manufacturing industries chimes more with the actual research need [30, 31]. The specific model is as follows:

$$\min \rho^{*} = \min \frac{1 - 1/W \sum_{w=1}^{W} s_{n}^{x} / x_{n}^{k}}{1 + \left[ 1/M + I\left( \sum_{m=1}^{M} s_{m}^{y} / y_{m}^{k} + \sum_{i=1}^{I} s_{i}^{b} / b_{m}^{k} \right) \right]}$$

$$s.t. \begin{cases} \sum_{k=1}^{K} z_{y}^{k} y_{m}^{k} - s_{m}^{y} = y_{m}^{k}, \quad m = 1, \dots, M, \\ \sum_{k=1}^{K} z_{y}^{b} b_{i}^{k} - s_{i}^{b} = b_{i}^{k}, \quad i = 1, \dots, I, \\ \sum_{k=1}^{K} z_{k}^{x} x_{w}^{k} - s_{w}^{x} = x_{w}^{k}, \quad w = 1, \dots, W, \\ z_{k}^{i} \ge 0, s_{m}^{y} \ge 0, s_{i}^{b} \ge 0, s_{w}^{x} \ge 0, \quad k = 1, \dots, K, \end{cases}$$

$$(1)$$

where  $\rho^*$  is the green innovation efficiency value of various industries in the manufacturing industry,  $s_m^y, s_i^b, s_w^x$  represent the slack variables,  $x_w^k, y_m^k, b_i^k$ , respectively, mean the input element, expected output, and unexpected output of the *k*th production unit; *W*, *M*, and *I*, respectively, equate the quantity of input factors, expected output, and unexpected output;  $z_k^x, z_y^k, z_y^b$ , respectively, denote the weight of the above three indicators. 2.2. Dagum Gini Coefficient Decomposition. Dagum Gini coefficient and its decomposition can measure the sources and contributions of green innovation efficiency development in various industries [32]. It can obtain the changing trend of the overall industry differences of the manufacturing industry in the sample period and reveal the intragroup and intergroup differences of grouped industries [33]. According to the subgroup decomposition method, this method can be divided into intragroup gap, intergroup gap, and supervariable density. The overall Gini coefficient is defined as formula (2) and the Gini coefficients within and between the groups as formulas (3) and (4). Among them, equation (3) represents the Gini coefficient  $G_{jh}$  of the industry group *j*, with (4) representing the Gini coefficient  $G_{jh}$  between the industry groups *j* and *h*.

$$G = \frac{\sum_{j=1}^{q} \sum_{h=1}^{q} \sum_{l=1}^{n_j} \sum_{r=1}^{n_j} \left| Y_{jl} - Y_{hr} \right|}{2n^2 \overline{Y}},$$
 (2)

$$G_{jj} = \frac{1/2\overline{Y_j} \sum_{l=1}^{n_j} \sum_{r=1}^{n_j} |Y_{jl} - Y_{jr}|}{n_j^2},$$
(3)

$$G_{jh} = \frac{\sum_{l=1}^{n_j} \sum_{r=1}^{n_h} \left| Y_{jl} - Y_{hr} \right|}{n_j n_h \left( \overline{Y_j} + \overline{Y_h} \right)},\tag{4}$$

where q represents the number of industry groups, n, the number of all industries,  $Y_{jl}$  and  $Y_{hr}$ , respectively, the green innovation efficiency values of l and r industries in j and h industry groups.  $n_j$  and  $n_h$ , the number of industries in the corresponding j and h groups, and  $\overline{Y}$ , the average value of green innovation efficiency of all manufacturing industries.  $\overline{Y_j}$  and  $\overline{Y_h}$  denote the average value of green innovation efficiency of set average value of green innovation efficiency of j and h industry groups.

The results of intraindustry gap  $G_w$ , interindustry gap  $G_{nb}$ , and hypervariable density  $G_t$  can be expressed as follows:

$$G_w = \sum_{j=1}^q G_{jj} P_j S_j, \tag{5}$$

$$G_{nb} = \sum_{j=2}^{q} \sum_{h=2}^{j-1} G_{jh} D_{jh} (P_j S_h + P_h S_j),$$
(6)

$$G_t = \sum_{j=2}^{q} \sum_{h=2}^{j-1} G_{jh} \Big( P_j S_h + P_h S_j \Big) \Big( 1 - D_{jh} \Big).$$
(7)

In equation (5),  $p_j = n_j/n$ ,  $s_j = n_j\overline{Y_j}/n\overline{Y}$ , j = 1,2, ..., q; in equations (6) and (7),  $D_{jh}$  is the relative influence of the green innovation efficiency between the industry groups j and h as shown in equation (8).  $d_{jh}$  represents the difference of green innovation efficiency among the industry groups, and the mathematical expectation of the sum of all the sample values of  $Y_{il}-Y_{hr}>0$  in the industry groups j and h as

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$$D_{jh} = \frac{(d_{jh} - p_{jh})}{(d_{jh} + p_{jh})},$$
(8)

$$d_{jh} = \int_{0}^{\infty} dF_{j}(Y) \int_{0}^{Y} (Y - x) dF_{h}(x),$$
(9)

$$p_{jh} = \int_{0}^{\infty} dF_{h}(Y) \int_{0}^{Y} (Y - x) dF_{j}(x).$$
(10)

In equations (9) and (10), the functions  $F_j$  and  $F_h$  represent the cumulative density distribution functions of the industry groups j and h.

2.3. Convergence Analysis Method. To analyze how green innovation efficiency differences in the manufacturing industries evolve, this paper applied  $\sigma$  and  $\beta$  convergences to investigate that of the green innovation efficiency in the Chinese manufacturing industry [34, 35].

 $\sigma$  convergence test model:  $\sigma$  convergence can be understood as a process with a continuous decline of the dispersion degree of green innovation efficiency in different industries over time. In this paper, the coefficient of variation method was used, and its calculation equation is as follows:

$$\sigma = \frac{\sqrt{\sum_{l}^{N_{j}} \left( PS_{lj} - \overline{PS_{lj}} \right) / N_{j}}}{\overline{PS_{lj}}},$$
(11)

where *j* represents the industry group, *l*, the industry included in the industry group,  $N_j$ , the number of industries included in the industry group *j*, and  $\overline{PS_{lj}}$ , the mean value of the green innovation efficiency of the industry group *j*.

 $\beta$  convergence test model:  $\beta$  convergence means that as time goes by, the industries that are low in green innovation efficiency but high in growth rate will overtake the efficient industries with a bridged gap and a consistent level. The different application preconditions enable the division of  $\beta$ convergence: absolute and conditional  $\beta$  convergences. In this paper, the industry convergence trend of the green innovation efficiency in the manufacturing industry is mainly studied based on the absolute  $\beta$  convergence without the influence of other factors on the industry green innovation efficiency. The absolute  $\beta$  convergence model is as follows:

$$\ln\left(\frac{PS_{l,t+1}}{PS_{l,t}}\right) = \alpha + \beta \,\ln(PS_{l,t}) + \mu_l + \eta_t + \varepsilon_{lt},\tag{12}$$

where *l* represents the industry (*l* = 1, 2, ..., *N*), *t* represents the time (*t* = 1, 2, ..., *T*).  $PS_{l,t+1}$ ,  $PS_{l,t}$ , respectively, equate the green innovation efficiency of industry *l* in *t*+1 and *t* periods;  $PS_{l,t+1}/PS_{l,t}$  denotes the annual growth rate of the green innovation efficiency of *l* industry from *t* to *t*+1.  $\beta$  is the convergence coefficient. If  $\beta < 0$  and passes the significance test, then it indicates that  $\beta$  convergence exists in the green

innovation efficiency of the Chinese manufacturing industry with its convergence rate expressed as  $v = -\ln(1+\beta)/T$ . If  $\beta > 0$ and passes the significance test, then divergence exists.  $\mu_l$ represents the individual effect of the industry,  $\eta_t$ , the time effect, and  $\varepsilon_{lt}$ , the interference terms obeying independently and identically distributed.

 $\sigma$  convergence emphasizes that the difference of green innovation efficiency in the manufacturing industries will become smaller with time, while  $\beta$  convergence is more focused on describing the convergence process from the angle of catching up than  $\sigma$  convergence, which can not only get the convergence situation of green innovation in the manufacturing industries, but also get the convergence speed.

# 3. Indicators and Data

The green innovation efficiency index should be selected in a scientific, objective, and truthful way with the real manufacturing efficiency in green innovation and the index data available. Therefore, this paper took the panel data of 29 industries in the Chinese manufacturing industry from 2010 to 2019 as samples and selected the workforce, capital, and energy input indicators to measure the green innovation efficiency of the manufacturing industry. Among them, the proxy variable of human input was the full-time equivalent of R&D personnel with the capital input characterized by three variables: internal expenditure of R&D funds, expenses of new product development funds, and technology introduction and transformation funds. Technology introduction and transformation funds equated the total cost of various industries with the energy input characterized by the total energy consumption.

The expected and unexpected outputs mainly measured the output indicators of green innovation. In this paper, two were selected as the expected output indicators: (1) the sales revenue of new products reflecting the market value transformation results of the industries; (2) the number of patent applications mirroring the independent innovation results of the industries. The pollutant index reproducing the natural environment of various industries in the innovative R&D activities was the unexpected output with industrial sulfur dioxide emissions, wastewater emissions, and general industrial solid waste production used to measure the environmental impact of green innovation activities in the manufacturing industry.

The index data in this paper are obtained from the relevant statistical yearbooks with their authenticity and reliability underpinning the research of this paper. The related indicators of human input, capital input, and expected output are from the 2011–2020 China statistical yearbook of science and technology. The energy input index comes from the 2011–2020 China energy statistical yearbook with the undesired output indicators from the 2011–2020 China environmental statistics yearbook. The descriptive statistics of the relevant indicators in 2019 are shown in Table 1.

Technology drives further innovation and quality development of the manufacturing industry, whose balanced

	Variables	Max	Min	Mean	Standard deviation
	Full-time equivalent of R&D personnel (man-year)		4256	104812	115387
	Intramural expenditure on R&D (10 000 yuan)		303865	4652828	5261353
Tomust maniable	Expenditure on new products development (10 000 yuan)	36778181	293783	5757977	7441695
input variable	Total expenditure on technology introduction and technological transformation (10 000 yuan)		30016	1347702	2142693
	Total energy consumption (104 tce)	65387	192	9232	16243
Expected output	Sales revenue of new products (10 000 yuan)	441509516	3540521	72037052	94928552
variable	Patent applications (piece)	204836	3277	35018	47170
TT	Industrial sulfur dioxide Emission (ton)	1037198	8	101176	234231
Unexpected output	Industrial waste water discharged (10 000 tons)	76977	240	14832	20702
variable	Common industrial solid wastes generated (10 000 tons)	56269	11	5463	12153
Expected output variable Unexpected output variable	technological transformation (10 000 yuan) Total energy consumption (104 tce) Sales revenue of new products (10 000 yuan) Patent applications (piece) Industrial sulfur dioxide Emission (ton) Industrial waste water discharged (10 000 tons) Common industrial solid wastes generated (10 000 tons)	65387 441509516 204836 1037198 76977 56269	192 3540521 3277 8 240 11	9232 72037052 35018 101176 14832 5463	16243 94928552 47170 234231 20702 12153

TABLE 1: The descriptive statistics of the evaluation index of the green innovation efficiency of manufacturing industry in 2019.

economic and environmental benefits hinge on the former with the latter's diversified call for ununiform technology needs. To better compare the green innovation efficiency of the manufacturing industries under different technology needs, this paper analyzed the overall differences of the green innovation efficiency among the disparate groups in the manufacturing industries. Based on the manufacturing industry classification in the organization for economic cooperation and development and relevant research, 29 manufacturing industries were divided into three groups, concerning R&D investment intensity: low-end, mid-end, and high-end technology industries. The low-end technology industry includes the processing of food from agricultural products (C13), manufacture of foods (C14), manufacture of liquor, beverages, and refined Tea (C15), manufacture of tobacco (C16), manufacture of textile (C17), manufacture of textile, wearing apparel, and accessories (C18), manufacture of leather, fur, feather, and related products and footwear (C19), processing of timbers and manufacture of wood, bamboo, rattan, palm, and straw products (C20), manufacture of furniture (C21), manufacture of paper and paper products (C22), printing and reproduction of recording media (C23), manufacture of articles for culture, education, arts and crafts, sport, and entertainment activities (C24), and other manufacture (C41). Mid-end technology industry includes the processing of petroleum, coal, and other fuels (C25), manufacture of rubber and plastic products (C29), manufacture of nonmetallic mineral products (C30), smelting and pressing of ferrous metals (C31), smelting and pressing of nonferrous metals (C32), and manufacture of metal products (C33). High-end technology industry includes the manufacture of raw chemical materials and chemical products (C26), manufacture of medicines (C27), manufacture of chemical fibers (C28), manufacture of general purpose machinery (C34), manufacture of special purpose machinery (C35), manufacture of automobiles (C36), manufacture of railway, ship, aerospace, and other transport equipment (C37), manufacture of electrical machinery and apparatus (C38), manufacture of computer, communication, and other electronic equipment (C39), and manufacture of measuring instrument and machinery (C40). Because of the various statistical calibers in the statistical yearbooks of different years, the utilization of waste resources (C42) and metal

products, machinery and equipment repair (C43) are incomprehensive during the sample study period. Hence, these two industries are excluded.

## 4. Results and Discussions

4.1. Efficiency Measurement and Analysis of Green Innovation in the Manufacturing Industry. By considering the Super-SBM model with the unexpected output and max data envelopment analysis software, the green innovation efficiency values of 29 industries, three major industry groups, and national manufacturing industries in China from 2010 to 2019 are calculated as shown in Table 2. For a clearer analysis of the development difference evolution in the green innovation efficiency about the three types of industry groups under different technical requirements, the time-series change diagram of the efficiency is drawn from the standpoint of the country and three major industry groups as shown in Figure 1. In addition, according to the efficiency classification basis of references [19], the efficiency value of green innovation is divided into high efficiency ( $\geq 0.9$ ), medium efficiency (0.5–0.9), and low efficiency ( $\leq 0.5$ ).

From an industry perspective, the average value of green innovation efficiency shows that over 75% of the Chinese manufacturing industries have a green innovation efficiency value of less than 1 in a DEA invalid state. In addition, the green innovation efficiency values of 29 industries are significantly different from each other. Only 7 industries, including C36, C38, C39, C40, C16, C21, and C24, owned over 1 green innovation efficiency value with a forefront efficiency throughout the study. The green innovation of 10 industries, C13, C17, C19, C22, C25, C32, C28, C34, C35, and C37, has reached an effective level in individual years without high efficiency all the time because of the influence of unstable factors in other years. Other invalid industries during the sample study period witnessed the five industries at the bottom: C31, C15, C30, C14, and C26; the green innovation efficiency values fluctuate between 0.2 and 0.35, with nearly 65%-80% room for improvement. It identified the redundancy in the innovation investment of these five industries, insufficient innovation output capacity, highly unexpected output, serious environmental pollution, and low green development level. The state should strengthen the innovation

TABLE 2: The calculation results of green innovation efficiency of 29 manufacturing industries from 2010 to 2019.

		0			,			U				
Industry codes	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019	Mean	Rank
C13	0.269	0.253	0.350	0.306	0.324	1.312	0.322	0.347	0.377	0.373	0.423	18
C14	0.281	0.189	0.270	0.286	0.263	0.266	0.279	0.280	0.284	0.296	0.269	26
C15	0.215	0.158	0.231	0.225	0.193	0.198	0.189	0.241	0.314	0.334	0.230	28
C16	1.124	1.185	1.198	1.256	1.229	1.218	1.198	1.348	1.287	1.327	1.237	2
C17	0.450	0.403	0.525	1.028	1.010	1.063	1.032	1.039	0.413	0.381	0.734	11
C18	1.003	0.560	1.023	1.014	1.042	1.040	1.035	1.033	1.035	1.048	0.983	8
C19	0.527	1.018	1.016	1.003	0.530	0.637	0.688	0.567	1.097	1.141	0.822	9
C20	0.393	0.274	0.350	0.313	0.349	0.338	0.286	0.290	0.402	0.457	0.345	23
C21	1.172	1.195	1.141	1.128	1.008	1.103	1.153	1.151	1.145	1.110	1.131	5
C22	0.235	0.188	0.239	0.329	0.242	0.440	0.369	0.427	1.023	0.524	0.402	19
C23	0.274	0.249	0.380	0.413	0.418	0.415	0.448	0.546	0.545	0.588	0.428	17
C24	1.152	1.117	1.140	1.118	1.128	1.121	1.067	1.048	1.044	1.029	1.097	6
C41	0.400	0.312	0.239	0.277	0.300	0.352	0.399	0.414	0.500	0.470	0.366	21
C25	0.135	0.112	0.165	0.235	0.192	1.096	0.216	0.214	1.025	1.029	0.442	16
C29	0.336	0.273	0.385	0.370	0.334	0.352	0.412	0.409	0.446	0.459	0.378	20
C30	0.216	0.166	0.239	0.272	0.266	0.292	0.245	0.299	0.339	0.353	0.269	27
C31	0.168	0.125	0.167	0.201	0.170	0.193	0.231	0.285	0.309	0.312	0.216	29
C32	0.237	0.230	0.237	0.353	0.335	0.374	0.414	1.003	1.023	1.006	0.521	15
C33	0.303	0.344	0.368	0.328	0.333	0.359	0.399	0.379	0.411	0.435	0.366	22
C26	0.180	0.178	0.229	0.291	0.225	0.314	0.289	0.356	0.432	0.360	0.285	25
C27	0.321	0.279	0.302	0.284	0.290	0.293	0.347	0.332	0.360	0.371	0.318	24
C28	0.264	0.312	0.415	1.006	1.000	0.443	0.427	1.000	1.039	1.076	0.698	12
C34	0.384	0.529	0.473	0.531	0.463	0.499	0.709	0.623	0.754	1.023	0.599	14
C35	0.423	0.499	0.561	0.608	0.532	0.600	1.094	1.034	1.069	1.029	0.745	10
C36	1.105	1.115	1.076	1.046	1.051	1.052	1.083	1.079	1.070	1.069	1.075	7
C37	0.458	0.502	0.466	0.462	0.472	0.564	0.797	1.006	0.661	1.023	0.641	13
C38	1.212	1.060	1.180	1.095	1.139	1.250	1.159	1.082	1.108	1.090	1.137	4
C39	1.299	1.236	1.234	1.139	1.140	1.139	1.188	1.091	1.091	1.085	1.164	3
C40	1.009	1.309	1.168	1.259	1.225	1.135	1.187	1.549	1.529	1.634	1.300	1
Low-end technology industry	0.577	0.546	0.623	0.669	0.618	0.731	0.651	0.672	0.728	0.698	0.651	(2)
Mid-end technology industry	0.233	0.208	0.260	0.293	0.272	0.444	0.319	0.432	0.592	0.599	0.365	(3)
High-end technology industry	0.665	0.702	0.711	0.772	0.754	0.729	0.828	0.915	0.911	0.976	0.796	(1)
All industries	0.536	0.530	0.578	0.627	0.593	0.671	0.644	0.706	0.763	0.774	0.642	_



FIGURE 1: The time-series diagram of green innovation efficiency of the whole country and three major industry groups.

output in these industries and promote the development of green industries through technological innovation and energy conservation and emission reduction. In view of different technology industry groups, during the sample study period, the mean value of the manufacturing green innovation efficiency in the three industry groups witnessed a high-to-low order: high-end technology industry group (0.796) > low-end technology industry group (0.651) > middle technology industry group (0.356). All of them with a DEA inefficiency possess different respective improvement spaces. The middle-end technology industry group with the lowest green innovation efficiency mainly covers the industries with high pollution and energy consumption, such as petroleum, coal, rubber, and metal processing. To improve the green innovation efficiency of the middle-end technology industry group, the most important thing is to control the pollution emissions of various industries from the perspective of reducing the unexpected output. In addition, Figure 1 unveils the consistency between the green innovation efficiency value of low-end technology industry groups and the national manufacturing industry changes, with the former witnessing a slow fluctuation upward trend and a stable medium efficiency level. The value of green innovation efficiency of the mid-end technology industry group increased from 0.233 in 2010 to 0.599 in 2019. Although it is far from the production frontier, the green innovation efficiency of the mid-end industry with a breaking-neck progress is overtaking the other two. Although the green innovation efficiency of the high-end technology industry group dropped slightly in 2014 and 2015, its value with the overall transformation jumped from 0.665 in 2010 to 0.976 in 2019, shifting from medium to high efficiency. The green innovation represents the core of the high-end technology industry that demands remarkable technological innovations and advanced technologies, better industry advancement environment, and the green development of the whole life cycle concerning products, production, sales, and transportation.

From the national level, the average green innovation efficiency of the manufacturing industry from 2010 to 2019, 0.642, is in the middle green innovation efficiency and does not reach the DEA effective level, indicating 35.8% improvement space. The change trend chart in Table 1 and Figure 1 unveils the swelling of the national green innovation efficiency of the manufacturing industry from 0.536 to 0.774 during the sample period with an obvious fluctuation upward trend and a certain gap with the optimal DEA efficiency. It shows that in the past decade, the policy on green innovation and manufacturing industry development has yielded desirable results with much attention paid to this area. Putting innovation at the core of the overall development of the manufacturing industry provides a favorable environment for its innovation and development and constantly pushes it from high-speed to high-quality development. As China steadily advances green innovation in the manufacturing industry according to its annual average growth rate during the sample study period, the manufacturing industry is expected to achieve a DEA effectiveness in 2026.

4.2. Industry Difference and Decomposition of Green Innovation Efficiency in the Manufacturing Industry. To further explain the development difference of green innovation efficiency in the manufacturing industry and reveal the overall difference and its source in the industry, the Dagum Gini coefficient method is used to measure the industry gap and subgroup decomposition division of green innovation efficiency in the Chinese manufacturing industry and three technology industry groups from 2010 to 2019 as shown in Figure 2.

The overall difference and evolution trend of green innovation efficiency in the Chinese manufacturing industry from 2010 to 2019 are displayed in Figure 2(a). Its overall gap fluctuated and declined with the general Gini coefficient *G* falling from 0.373 in 2010 to 0.264 in 2019. The prevalent contracted disparities between the manufacturing industries indicate that the manufacturing enterprises emphasized green innovation, the main driving force for manufacturing transformation and development nationwide. China has enjoyed certain fruits in promoting the green transformation and high-quality development of the manufacturing sector.

Figure 2(b) reveals the intraindustry differences and evolution trend of the green innovation efficiency in the manufacturing industry with the higher intragroup difference of a low-end technology industry group than that of the other two counterparts. The average Gini coefficient order of various industry groups: low-end technology industry group (0.319) > high-end technology industry group (0.256) > midend technology industry group (0.208). According to the evolution trend of each industry group, the low-end technology industry group showed a trend of slight fluctuation and decline with the biggest difference in 2011. The largest discrepancy in the low-end technology industry can be understood by the balanced development of green innovation in the high-efficiency industry and the massive environmental pollution in the lower one with more daunting polarization left in the low-end technology industry. The large change range in the intraindustry gap of the mid-end technology industry group reveals an inconspicuous consistent change trend. Before 2014, the smallest difference of green innovation efficiency in the mid-end technology industry group fluctuated greatly between 2014 and 2017, and later, it crept up, with the biggest difference in 2015. However, given the low efficiency and unbalanced differences in the mid-end technology industry group, it is necessary to move toward high-efficiency and balanced development through coordinated technological innovation and green advancement. The biggest difference in the highend technology industry group in 2010 was followed by a continuous decline trend with a large drop unveiling slight discrepancies within the high-end group. As all industries emphasize green innovation progress, the favorable environment of mutual assistance and promotion within the industry group was established, pushing the high-end technology industry group to strengthen innovation and control pollution simultaneously.

Figure 2(c) shows the interindustry differences and evolution trend of green innovation efficiency in the manufacturing industry. The evolution trend unveiled a consistent decreasing fluctuation in the differences among the industry groups with various fluctuation amplitudes. The largest difference recorded between the mid-end technology industry group and the high-end counterpart saw a drop



FIGURE 2: The time-series diagram of green innovation efficiency of the whole country and three major industry groups. (a) Overall differences in green innovation efficiency in manufacturing industries. (b) Intraindustry differences in green innovation efficiency of manufacturing industry. (c) Interindustry differences in green innovation efficiency of manufacturing.

from 0.501 in 2010 to 0.302 in 2019, the fastest decline among the three groups. The smallest difference between the lowend and high-end groups witnessed a small change range and a slow decline rate. The same between the low-end and mid-range technology industry groups gradually narrowed over time. In 2019, the intergroup difference of the industry groups was approximately 0.3, with a progressively same level of difference, specifically. The differences between the industry groups knitted with the development environment of each one. The high-end technology industry groups excel at innovation and development, with great leading technological advantages and industrial integration. In comparison, the middle and low-end groups are uncompetitive in resources such as research and development and environmental pollution treatment, with subsequent large differences among groups incurred.

The source decomposition and contribution results of industrial differences in the green innovation efficiency of the Chinese manufacturing industry are shown in Table 3. The contribution rate of different sources indicates the discrepancies between the groups mainly caused by the overall green innovation efficiency inconsistency in the Chinese manufacturing industry with an average contribution rate of 38.528%. The intragroup differences are the second source of overall inconsistencies with an average contribution rate of 33.159%. The lowest contribution rate of the supervariable density registered a moderate rate of only 28.313%. From the evolution trend, the overall contribution rate of the intragroup differences showed a steady change trend with the contribution rate ranging from 32.01% to 34.857%. The contribution rate of intergroup difference, the largest before 2014 with a small fluctuation range has experienced a W-shaped change, with a great fluctuation since 2015. The contribution rate of the supervariable density variance, the lowest before 2014, with a small fluctuation spectrum, showed an M-shaped change trend with a fluctuation range increased from 2015 to 2019. It should be further explained that the overall difference of the green innovation efficiency in the manufacturing industry changed from the supervariable density difference in 2015 and 2018, reflecting the contribution rate of the cross-overlap of different industry groups to the overall difference.

4.3. Convergence Analysis of Green Innovation Efficiency of Chinese Manufacturing Industry. For a more accurate

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Years	Total C		Contribution			Contribution rate (%)		
	Iotal G	$G_w$	$G_{nb}$	$G_t$	$G_w$	$G_{nb}$	$G_t$	
2010	0.373	0.126	0.143	0.104	33.867	38.291	27.842	
2011	0.405	0.135	0.171	0.099	33.379	42.252	24.369	
2012	0.356	0.119	0.137	0.099	33.490	38.561	27.949	
2013	0.331	0.108	0.136	0.087	32.766	41.010	26.224	
2014	0.346	0.114	0.147	0.085	32.886	42.620	24.495	
2015	0.314	0.109	0.070	0.134	34.857	22.412	42.731	
2016	0.319	0.102	0.147	0.070	32.028	45.935	22.037	
2017	0.305	0.098	0.134	0.074	32.010	43.818	24.172	
2018	0.263	0.090	0.083	0.090	34.091	31.736	34.173	
2019	0.264	0.085	0.102	0.077	32.218	38.649	29.133	

TABLE 3: Source decomposition and contribution results of the industrial differences in the green innovation efficiency of manufacturing industry.

Note.  $G_w$  is the intragroup difference.  $G_{nb}$  is the intergroup difference.  $G_t$  is the supervariable density difference, satisfying  $G = G_w + G_{nb} + G_t$ .

TABLE 4:  $\sigma$  value of green innovation efficiency of manufacturing industry in China and three major industry groups.

Vears	National manufacturing	Low-end technology industry	Mid-end technology industry	High-end technology industry	
1 cars	industry	group	group	group	
2010	0.727	0.666	0.331	0.655	
2011	0.776	0.767	0.435	0.614	
2012	0.677	0.650	0.368	0.567	
2013	0.621	0.618	0.231	0.484	
2014	0.650	0.639	0.277	0.519	
2015	0.579	0.567	0.734	0.511	
2016	0.589	0.594	0.306	0.441	
2017	0.562	0.583	0.669	0.408	
2018	0.483	0.515	0.571	0.391	
2019	0.494	0.530	0.549	0.379	

examination of the evolution trend of green innovation efficiency in various industries, the paper focuses on the convergence mechanism analysis of the green innovation efficiency across multiple manufacturing industries, resting on the study of green innovation efficiency level and difference decomposition in the Chinese manufacturing industry.

4.3.1.  $\sigma$  Convergence Analysis of Green Innovation Efficiency in Manufacturing Industry. In this paper, the coefficient of variation method is used to analyze the  $\sigma$  convergence of the green innovation efficiency of the Chinese manufacturing industry during the observation period. The results shown in Table 4 unveil that except the middle-end technology industry group, the national manufacturing industry, the lowend group, and the high-end group underwent a downward trend of fluctuation. The results show the inconsistent convergence of  $\sigma$  in the sample period with the features of intermittent convergence with changes. The expanded differences in some years existed with the unchanged overall downward trend. As far as the mid-end technology industry group is concerned, the green innovation efficiency of various industries exhibited an inconsistent convergence trend with irregular and divergent variation trends in 2011, 2014, 2015, and 2017. The gradually decreasing  $\sigma$  value from

2017 to 2019 witnessed the signs of  $\sigma$  convergence with the higher coefficient of 0.549 in 2019 than that of 2010–2014.

4.3.2. Absolute  $\beta$  Convergence Analysis of Green Innovation Efficiency in Manufacturing Industry. The STATA software is used in this paper for data analysis with the regression results shown in Table 5. The green innovation efficiency of the whole country and three major industry groups in the sample period witnessed inconsistency between its absolute  $\beta$  convergence model and the original hypothesis during model estimation. Therefore, the fixed effects model tested the absolute  $\beta$  convergence of the green innovation efficiency in the manufacturing industry.

The regression results in Table 4 revealed the  $\beta$  coefficient of green innovation efficiency of the national manufacturing industry and the three major industry groups below 0, which have passed the 1% significance level test. It shows that under the similar external environment and influencing factors, the green innovation efficiency of the whole manufacturing industry and the three major industry groups in China have an absolute  $\beta$  convergence phenomenon with a narrowing industry gap. The result chimes with the difference decomposition of the Dagum Gini coefficient mentioned above. The convergence speed of the national manufacturing industry is 0.0668 with the convergence speeds of low, medium, and

Coefficients	National manufacturing industry	Low-end technology industry group	Mid-end technology industry group	High-end technology industry group
β	-0.4872*** (-8.25)	-0.6288*** (-6.73)	-0.4290*** (-3.21)	-0.3727*** (-4.43)
α	-0.2766*** (-6.34)	-0.3715*** (-5.77)	4238** (-2.47)	-0.0936** (-2.35)
Time effect	YES	YES	YES	YES
Individual effect	YES	YES	YES	YES
Sample numbers	261	117	54	90
R-squared	0.2275	0.3057	0.1795	0.1987
F-value	68.04***	45.35***	10.28***	19.59***

TABLE 5: Absolute  $\beta$  convergence regression results of green innovation efficiency of manufacturing industry and industry groups in China.

Note.  $\beta$  is the coefficient of observation. \*\*\*, \*\*, and \* mean significant at the level of 1%, 5% and 10% respectively. Figures in parentheses are *T* values.  $\alpha$  is the constant term.

high-end technology industry groups to be 0.0991, 0.0560, and 0.0466, respectively. It means there is a slower convergence speed in the high-end group with a higher green innovation efficiency followed by the middle-end one and with the low-end counterpart enjoying the fastest convergence speed. It indicates that the faster growth of the industries with a low green innovation efficiency in the manufacturing industry than that of the industries with a high efficiency has gained a certain catch up momentum, with the green innovation efficiency of different manufacturing industries converging to the same steady-state level over time.

#### 5. Conclusions and Policy Recommendations

Based on the panel data of 29 industries in the national manufacturing industry from 2010 to 2019, this paper analyzes the green innovation efficiency, industry development differences, and the convergence mechanism of manufacturing industries with the super-SBM model, Dagum Gini coefficient decomposition method, and convergence model. The main research conclusions are as follows:

Firstly, the manufacturing green innovation efficiency nationwide increases incessantly with an obvious efficiency difference between 29 industries, three-quarters of the industries in low efficiency, and a large green innovation efficiency improvement space.

Secondly, the green innovation efficiency of different technology industry groups with an annual growth and significant edges in the high-end technology industry group basically shifted from medium to high efficiency. The midend and low-end technology industry groups still focus on the green innovation development of the Chinese manufacturing industry.

Thirdly, the  $\sigma$  and  $\beta$  convergences from the time dimension reveal that the green innovation efficiency of the national manufacturing industry and the low-end and highend technology industry groups all show an intermittent  $\sigma$  convergence trend with the minimum and divergent convergence characteristics of the middle-end ones. For an absolute  $\beta$  convergence, there is a significant trend of an absolute  $\beta$  convergence in the green innovation efficiency of the national manufacturing industry and the three industry groups with diversified convergence rates.

Given the above conclusions with the actual green innovation efficiency of the manufacturing industries in China, to transform the manufacturing industry, enhance its green innovation capability, and achieve its high-quality development, this paper puts forward the following policy recommendations:

The government should formulate appropriate green innovation policies to enhance the green innovation capability of its manufacturing industry that is set apart from that of other sectors with differentiated development strategies for related industries. Relevant departments need to transform the government functions to give full play to the guiding role of the government in promoting green technology innovation of enterprises. For the low-end technology industry group, the strengthened informatization investment should be accompanied by improved product technology, energy efficiency, and environmental protection through policy support. For the middle one, appropriate policies should be adopted to adjust traditional production and operation modes, by means of advanced technology to improve the production process of enterprises and their green management implementation and form a green manufacturing system. For the high-end counterpart, government financial subsidies will accelerate the research and development of innovative technologies and comprehensively promote its high-quality development. The high-end will lead the national manufacturing industry to make breakthroughs in innovation and green development.

All industries should work together to improve the green innovation environment that boosts industrial transformation. To improve its overall efficiency, the national manufacturing industry should focus on optimizing the environment for green innovation, and promoting all industries to uphold the green innovation development, with increasing awareness of in all sectors. The state should increase funding and support for green innovation with the wide application of green technologies. All industries should build an exchange platform for sharing green technologies and exchanging innovative talents in the manufacturing industry, promote open innovation, scientific and technological cooperation to ensure the effective transformation of green innovation achievements in various sectors. Moreover, the manufacturing industry transformation should be encouraged from policies, talents, technology, and environment with foreign advanced green innovation development models.

However, this research has some limitations. In the analysis of  $\beta$  convergence characteristics, this paper mainly studies the industry convergence trend of green innovation efficiency of manufacturing industry with absolute  $\beta$  convergence, without considering the external environment of the development of various industries. In future studies, the influence of various external factors on the industry green innovation efficiency will be considered, and further analysis through conditional  $\beta$  convergence model to grasp the industry convergence characteristics of the green innovation efficiency of the manufacturing industry in China will be made more comprehensively.

# **Data Availability**

The data used to support the findings of this study are available from the corresponding author upon request.

# **Conflicts of Interest**

The authors declare that this manuscript has not been published elsewhere or under consideration in any journal. The authors declare no conflicts of interest.

#### Acknowledgments

This research was funded by the Tianjin Science and Technology Program (18ZLZDZF00190); Tianjin Science and Technology Program (18ZLZXZF00390); and Humanities and Social Sciences Planning Fund Project of the Ministry of Education (20YJA630085).

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