Research Article

Evaluation of Manufacturing Innovation Performance in Wuhan City Circle Based on DEA-BCC Model and DEA-Malmquist Index Method

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The innovation performance of the manufacturing industry in the Wuhan city circle is evaluated based on the relevant data from 2018 to 2020 in 9 cities of Hubei Province within the Wuhan city circle using the DEA-BCC model, the DEA-Malmquist index method, and the location quotient method. This article measures the agglomeration level of innovation elements in the Wuhan city circle, constructs a performance evaluation index system including two input indicators: R&D expenditure and R&D personnel, and two output indicators: new product sales revenue and number of patent applications; evaluates the innovation performance of 27 manufacturing industries in the Wuhan city circle from five aspects: technical efficiency change (effch), technical progress change (techch), pure technical efficiency change (pech), scale efficiency change (sech), and total factor productivity change (tfpch), and compares and analyzes the innovation performance of Wuhan, Xianning, Xiantao, and Tianmen using the DEA-BCC model and DEAP 2.1. The results show that the agglomeration level of talent elements in the Wuhan city circle is between 0.24 and 1.75, and the agglomeration level of capital elements is between 0.23 and 1.52. The differences between regions are obvious, the degree of coordination is low, and the radiation effect of Wuhan is insufficient. The average value of technological progress is 1.274, which is vital to enhance the innovation performance of the Wuhan manufacturing industry. The technical efficiency dropped by 65%, but the total factor productivity fell only 13%, indicating that the technical efficiency value is not the main factor affecting the innovation performance of Wuhan. The innovation performance of high-tech and high-value-added industries such as computer, communication, and other electronic equipment manufacturing industries is relatively high, while the innovation performance of low-tech and low-value-added industries such as agricultural and sideline food processing industry and textile industry is relatively low. The innovation performance of Xianning, Xiantao, and Tianmen is higher, while the relative technological inefficiency caused by the low-scale efficiency value adversely affects the innovation performance of Wuhan. The results indicate that increasing the scale of manufacturing innovation investment can effectively enhance the innovation performance of the Wuhan city circle manufacturing industry.

1. Introduction

In April 2021, the Guiding Opinion on Promoting the High-quality Development of the Central Region in the New Era issued by the Central Committee of the Communist Party of China and the State Council provided a strong impetus to promote the rise of the Central region. The national 14th Five-Year Plan and the outline of the long-term goals for 2035 clearly pointed out that it is necessary to speed up the construction of Wuhan city circle and create a significant national growth pole. On May 19, the first joint meeting of Wuhan city circle reached an agreement on the urban integration development of 9 cities for the first time, which included program co-editing, transportation conetwork, technology codevelopment, industry cochain, and people’s livelihood coguarantee. Specifically, program co-editing is the guide, transportation conetwork is the foundation, technology codevelopment is the core, industry cochain is
the support, and coguarantee of people’s livelihood is the goal. On the 4th of September, the listing of Wuhan City Circle Intercity Development Office provided an organizational guarantee for the integration development of the Wuhan city circle.

As the principle part of the real economy, the development of the manufacturing industry directly represents the economic and technological strength of a country or a region. Meanwhile, the level of innovation and development of the manufacturing industry is the key to improving a country’s core competitiveness and global impact. At present, although the development pattern of the Wuhan city circle is formed as R&D in Wuhan, manufacturing in the city circle, and the industrial system of main chain in Wuhan, supporting the city circle has begun to take shape. There are still some problems in practice, such as insufficient innovation guidance and low quality of development. The effective solution of the above problems requires a realistic understanding of the innovation performance of the manufacturing industry in the Wuhan city circle. Therefore, on the basis of clarifying the current situation of the manufacturing industry in the Wuhan city circle, this article measures and analyzes the innovation performance of the Wuhan city circle manufacturing industry employing DEA-BCC model, DEA-Malmquist index method, and location quotient analysis method. The conclusions can provide reference for the formulation of relevant policies.

2. Literature Review

The theory of innovation was first put forward by the American-Austrian economist Joseph Schumpeter in his masterpiece *The Theory of Economic Development* in 1911. Schumpeter believed that innovation was the use of new ways to achieve a new combination of production factors and production conditions and to make it an important component of the production system. Schumpeter pointed out that the innovation mainly included the following contents: manufacturing a new product, adopting a new production method, opening up a new market, developing a new supplier, and constructing a new organizational model [1]. Subsequently, scholars from various countries have carried out extensive and in-depth research on innovation. Stoneman believed that technological innovation was a complete process of introducing scientific inventions into the manufacturing system, developing them, and finally producing economic and trade behaviors for the first time [2]. Kanter believed that innovation was not limited to generating new ideas, technologies, or management, and combining and improving old ideas and concepts could also be called innovation [3].

Innovation performance is the concentrated expression of the results of innovation activities, the production efficiency shown by the input of a certain amount of innovation resource elements, and the result of cooperation and interaction between the various components of the innovation system [4]. Since the 1950s, academia has carried out extensive research on innovation performance. Regarding the connotation of innovation performance, scholars around the world have different views, but the more common view is to interpret innovation performance as the efficiency and effect of innovation, that is, the efficiency of transforming innovation input into results and the economic benefits brought by the achievement of results [5]. Hagedoorn et al. pointed out that the ratio of new products, new equipment, or new processes put into production was technical innovation performance in a narrow sense, while the relationship among R&D investment, patent application, and new product creation constituted was a broad concept of technical innovation performance [6]. Guan and Chen divided innovation performance into absolute result performance and relative efficiency performance [7]. Anthony and Rene believed that environmental innovation performance included three aspects: indirect performance, direct performance, and knowledge output. Among them, indirect performance referred to the utilization rate of scientific research equipment and the improvement of R&D efficiency, while direct performance was mainly reflected by achievement transformation benefits and the number of incubating enterprises. And the knowledge output included the number of patents and academic papers [8].

In the application research of the DEA method, Georgiou and Roessner reviewed several methods of technical efficiency assessment and focused on the comprehensive application of data envelopment and statistical methods [9]. Nsierowski and Arcelus used the DEA method to empirically analyze the innovation performance of 45 countries and regions [10]. Chen and Ali used the DEA-Malmquist index method to evaluate and analyze the technical efficiency of the computer industry [11]. Thompson employed the DEA model and the Malmquist index to evaluate the economic growth, competition, and technological efficiency of China’s major cities [12]. Qian and Chen applied the DEA model to study the technological innovation efficiency of China’s high-tech industry from 2009 to 2011 [13]. Chai et al. employed the DEA method to evaluate the technological innovation performance of six resource-based enterprises in China [14]. Yi and Chen utilized the DEA method and the Malmquist index method to evaluate the innovation performance of some countries [4]. Long et al. adopted the BCC model in the DEA method to measure the comprehensive efficiency, scale efficiency, and pure technical efficiency of regional innovation in electronics and communication equipment manufacturing industry in China [15]. Pan et al. used the DEA-Malmquist index method to study the sustainable development and efficiency of digital agriculture in China [16].

In summary, scholars have done plenty of research on innovation performance and innovation performance evaluation methods, which also provides a solid theoretical basis for this article. At present, the data envelopment analysis method is widely used in the innovation performance evaluation of countries, regions, industries, and enterprises. This method has the advantages of objectiveness and low error rate, especially in the performance evaluation of multi-input and multi-output. With the rapid development of regional integration, the application of DEA method to the evaluation of innovation performance in urban circles...
is not only necessary in the times, but also feasible in the method. And the research conclusions also have certain application value.

3. Data and Methods

3.1. Location Quotient. Location quotient (LQ) is often used to measure the agglomeration level of innovative elements [17, 18]. Location quotient is also known as specialization rate, where “quotient” is the result of division [19]. This method was first developed by the American economist Haggett and used to measure the relative concentration of a region and the level of specialization of an industry in a particular research area [20]. The formula for the location quotient is

\[ LQ_{ij} = \frac{q_{ij}/q_j}{q_i/q}, \]

where \( LQ_{ij} \) indicates the location quotient of industry \( i \) in region \( j \) of the country, \( q_{ij} \) is the relevant indicators of industry \( i \) in region \( j \), \( q_j \) is the relevant indicator of all industries in region \( j \), \( q_i \) is the relevant index of industry \( i \) nationwide, and \( q \) is the relevant index of all industries in the country. In the specific calculation of this article, two indicators are included: the location quotient of talent elements and the location quotient of capital elements. The size of the location quotient value represents the level of agglomeration of innovation elements. If the location quotient is greater than 1, it means that the degree of agglomeration of innovation elements is higher than the national average level of similar elements. If the location quotient is equal to 1, it means that the degree of agglomeration of innovation elements is the same as the national average of similar factors. If the location quotient is less than 1, it means that the concentration of innovation factors is lower than the national average of similar factors.

3.2. Data Envelopment Analysis. Data envelopment analysis (DEA) was first proposed in 1978 by renowned operations research scientists Chames, Cooper, and Rhode as an important nonparametric method for evaluating productivity [21]. The principle of this method is mainly to determine the relatively effective production frontier with the help of a mathematical programming method by keeping the input or output of decision-making unit (DMU) unchanged, project each decision unit to the production frontier of DEA, and evaluate their relative effectiveness by comparing the degree to which decision-making units deviate from the DEA frontier. This method is suitable for evaluating the efficiency of decision-making units with multiple inputs and multiple outputs, and can also be used to analyze the reasons and degrees of inefficiency of decision-making units through redundant inputs or insufficient outputs, to provide information for decision-making subjects [22]. Originally used by Chames to measure the efficiency of public sector and nonprofit organizations, the DEA model has been widely used in efficiency evaluation in banks, universities, hospitals, insurance companies, manufacturing, service industries, and many other fields. In the DEA method, the two most basic models are the CCR model and the BCC model, of which the input-oriented CCR model is the earliest and most widely used.

Assuming there are \( n \) decision units, each decision unit has \( m \) inputs to obtain \( s \) kinds of output. \( x_{ij} \) is the \( i \)-th input corresponding to the \( j \)-th decision-making unit and is no less than 0. \( y_{ij} \) is the \( s \)-th output corresponding to the \( j \)-th decision-making unit and is no less than 0. \( v_i \) and \( u_i \) are the weights of the input of the \( i \)-th input and the \( r \)-th output, respectively. Now let

\[
\begin{align*}
X_j &= (X_{1j}, X_{2j}, \ldots, X_{mj})^T, \quad j = 1, 2, \ldots, n, \\
Y_j &= (Y_{1j}, Y_{2j}, \ldots, Y_{mj})^T, \quad j = 1, 2, \ldots, n, \\
v &= (v_1, v_2, \ldots, v_m)^T, \\
u &= (u_1, u_2, \ldots, u_m)^T.
\end{align*}
\]

The efficiency evaluation index of the decision unit \( j \) is

\[ h_j = \frac{\sum_{i=1}^{n} u_i v_{r_{ij}}}{\sum_{i=1}^{m} v_i x_{ij}}. \]

Take the weights \( v \) and \( u \) as variables, use the efficiency index \( h_j \leq 1, j = 1, 2, \ldots, n \) as a constraint, take the efficiency index \( h_0 \) of the \( j_0 \)-th decision unit as the decision goal, evaluate the relative efficiency of the \( j_0 \)-th decision unit, and build the model as follows:

\[
\begin{align*}
\max \quad & \frac{u^Tv_{j0}}{v^Tx_{j0}} = V_p, \\
\text{s.t.} \quad & \frac{u^Tv_j}{v^Tx_j} \leq 1, \quad j = 1, 2, \ldots, n, \\
& v \geq 0, u \geq 0.
\end{align*}
\]

Let \( t = 1/v^Tx_{j0} \omega = tv \), and \( \mu = tu \).

The above fractional programming \((P_{C_R})\) is further converted to a corresponding equivalent linear programming \((P_{C^2R})\) as follows:

\[
\begin{align*}
\max \quad & u^T v_{j0} = V_p, \\
\text{s.t.} \quad & \omega^Tx_j - \mu^Tv_j \geq 0, \quad j = 1, 2, \ldots, n, \\
& \omega^Tx_{j0} = 1, \\
& \omega \geq 0, \mu \geq 0.
\end{align*}
\]

If the optimal solution of \((P_{C^2R})\) satisfies \( V_p = \mu^Tv_{j0} = 1 \), the decision unit is DEA valid.

3.3. DEA-Malmquist Index Method. To carefully examine the dynamic changes in R&D innovation efficiency under the condition of changes in production technology, it is necessary to further introduce the Malmquist index of R&D innovation, that is, to use the distance function to find the
Malmquist productivity index that can be used for vertical comparative analysis [22, 23].

Suppose there are \( n \) decision units, and each decision unit obtains \( s \) kinds of output with \( m \) inputs in the \( t \) period. \( x_t^j = (x_{t1}^j, x_{t2}^j, \ldots, x_{tm}^j) \) represents the input indicator value of the \( j \)th decision unit in period \( t \), and \( y_t^j = (y_{t1}^j, y_{t2}^j, \ldots, y_{ts}^j) \) represents the output indicator value of the \( j \)th decision unit in period \( t \), and they are all positive numbers and \( t = 1, 2, \ldots, T \).

In the case of constant returns to scale, let the distance function of \((x^t, y^t)\) in the \( t \)th period \( D_C^t(x^t, y^t) \) and in the \((t+1)\)th period \( D_C^{t+1}(x^{t+1}, y^{t+1}) \). Then, let the distance function of \((x^{t+1}, y^{t+1})\) in the \( t \)th period \( D_C^t(x^{t+1}, y^{t+1}) \) and in the \((t+1)\)th period \( D_C^{t+1}(x^{t+1}, y^{t+1}) \).

In the case of variable returns to scale, let the distance function of \((x^t, y^t)\) in the \( t \)th period \( D_V^t(x^t, y^t) \) and in the \((t+1)\)th period \( D_V^{t+1}(x^{t+1}, y^{t+1}) \). Then, let the distance function of \((x^{t+1}, y^{t+1})\) in the \( t \)th period \( D_V^t(x^{t+1}, y^{t+1}) \) and in the \((t+1)\)th period \( D_V^{t+1}(x^{t+1}, y^{t+1}) \).

Under the technical conditions of period \( t \), the change in the technical efficiency from period \( t \) to period \( t+1 \) is
\[
M^t = \frac{D_C^t(x^{t+1}, y^{t+1})}{D_C^t(x^t, y^t)} \quad (6)
\]

Under the technical conditions of period \( t+1 \), the change in the technical efficiency from period \( t \) to period \( t+1 \) is
\[
M^{t+1} = \frac{D_C^{t+1}(x^{t+1}, y^{t+1})}{D_C^{t+1}(x^t, y^t)} \quad (7)
\]

The change in productivity from period \( t \) to period \( t+1 \) can be obtained by calculating the geometric average of the above two Malmquist productivity indices:
\[
M = (x^t, y^t, x^{t+1}, y^{t+1}) = \sqrt{M^t \times M^{t+1}} = \sqrt{\frac{D_C^t(x^{t+1}, y^{t+1})}{D_C^t(x^t, y^t)} \times \frac{D_C^{t+1}(x^{t+1}, y^{t+1})}{D_C^{t+1}(x^t, y^t)}} \quad (8)
\]

The Malmquist index reflects the relative efficiency of a decision unit in two periods. If the Malmquist index is greater than 1, it means that the efficiency level from period \( t \) to period \( t+1 \) has increased. While if the Malmquist index is less than 1, it indicates a decline from period \( t \) to period \( t+1 \). And if the index equals to 1, it means no change.

Under the assumption of constant returns to scale, changes in productivity are influenced by technological progress and technological efficiency changes, and the Malmquist index can be expressed as a multiplication of the Technological Efficiency Change Index (TEC) and the Technological Progress Index (TE), that is, \( M(x^t, y^t, x^{t+1}, y^{t+1}) = TEC \times TE \).

Assuming variable returns to scale, the technical efficiency change (\( \Delta TEC \)) can be further decomposed into the product of a pure change in technical efficiency (\( \Delta TE \)) and a change in returns to scale (\( \Delta ASE \)). The Malmquist index can be further broken down into a combination of the Technological Progress Index, the Pure Technical Efficiency Index, and the Scale Efficiency Index, that is, \( M(x^t, y^t, x^{t+1}, y^{t+1}) = TEC \times TE = (PTE \times SE) \times TE \).

In summary, the specific meaning of the Malmquist index is shown in Table 1.

3.4. Data Sources. We take the manufacturing innovation data of the Wuhan city circle from 2018 to 2020 and the innovation data of 27 manufacturing subsectors in Wuhan as samples. In terms of input factors, the academia generally divides innovation investment into two levels: personnel investment and capital investment. In the evaluation of innovation performance, \( R&D \ Personnel \) is usually selected to measure the personnel input of innovative activities, and \( Internal\ Expenditure\ of\ R&D\ Funds \) is used to measure the capital investment of innovative activities. In terms of output elements, the outputs of innovative activities are usually divided into direct output and indirect output. The technical output of innovative activities is usually expressed as \( The\ Number\ of\ Patent\ Applications\ and\ The\ Number\ of\ Patents\ Granted \). Among them, \( The\ Number\ of\ Patent\ Applications\ can\ reflect\ the\ invention\ and\ innovation\ information\ more\ comprehensively\ and\ plays\ an\ important\ role\ in\ the\ development\ of\ new\ products\ and\ technological\ transformations\ \[24, 25\]. In addition, \( New\ Product\ Sales\ Revenue\ can\ intuitively\ reflect\ the\ innovative\ achievements\ of\ the\ industry,\ which\ is\ also\ included\ in\ the\ output\ index\ in\ this\ article.\n
4. Results and Discussion

4.1. Measurement and Analysis of Innovation Elements

4.1.1. The Level of Talent Element Agglomeration. Agglomeration Level

According to (1), the results of the concentration level of talent elements are calculated in Table 2.

It can be observed from Table 2 that the level of talent agglomeration in Wuhan and Huangshi was higher, and the agglomeration level of Huangshi in 2019 reached 1.75, which was much higher than the other cities. This is because both cities are located in the core area of the urban circle. Besides, Wuhan, as the central city of the urban circle, brings together many scientific and technological enterprises, and as the innovation engine of the Wuhan city circle, there are more than 7,000 overseas talent teams innovating and starting businesses here. In 2020, the levels of talent agglomeration in Wuhan, Huangshi, and Xiantao were in a higher range, while those in Tianmen and Ezhou were in a lower range. The overall level of talent agglomeration in Wuhan, Huangshi, Ezhou, and Qianjiang registered different degrees of decline from 2018 to 2020.

4.1.2. The Level of Capital Elements Agglomeration. Similarly, according to (1), the aggregation level of capital elements is calculated as shown in Table 3.

It can be seen from Table 3 that the agglomeration level of innovative capital elements in Wuhan, Huangshi, and Xiaogan was above 1 in 2018 and that in Huangshi even
reached 1.52, whereas the agglomeration level of innovative capital elements in Xiantao and Tianmen was below 0.5, which was at a low level. In 2020, the agglomeration level of Huangshi, Ezhou, and Xiaogan was higher than 1, of which the highest concentration level of Huangshi was 1.48. Compared to the situation in 2018, only Tianmen had a concentration level lower than 0.5 in 2020. In general, the level of capital agglomeration in Tianmen and Xiantao was low; Wuhan, Ezhou, Xianning, and Qianjiang were at a medium level; and Huangshi and Xiaogan were at a higher level.

4.2. Evaluation and Analysis of Manufacturing Innovation Performance in Wuhan

4.2.1. Overall Analysis. In this section, DEAP2.1 is used, and the DEA-Malmquist index model is selected for calculation based on the input and output data of Wuhan’s manufacturing industry from 2018 to 2020. Through this model, innovation performance can be evaluated from five aspects, that is, effch, techch, pech, sech, and tfpch, respectively. The results are shown in Table 4.

As can be seen from Table 4, total factor productivity (TFP) declined slightly in 2020 compared to 2018 and 2019, but overall, it was still between 1.0 and 1.1. The main reason for the decline in manufacturing innovation performance in 2020 may be from the impact of the COVID-19 pandemic. Total factor productivity is decomposed into technological progress and technological efficiency, and then reasons for its changes are explored. Through decomposition, it can be observed that although the value of technological progress has still declined, the arithmetic average was 1.274, which showed that the effect of technological progress on changes in total factor productivity was positive in the case of a significant reduction in other basic factors. Secondly, the technical efficiency fell from 1.443 to 0.511, a decline of about 65%, but the total factor productivity did not decline in the same proportion. The arithmetic average of technical efficiency in 2019 and 2020 was 0.859, and the average arithmetic value of total factor productivity was 1.094, indicating that the technical efficiency value was not the main reason affecting the innovation performance in Wuhan. The technical efficiency value is divided into pure technical efficiency value and scale efficiency value. The pure technical efficiency value varied from 0.6 to 1.1, and the impact on innovation performance was not significant, while the scale efficiency value varied from 0.7 to 1.3, resulting in the corresponding diseconomies of scale.

4.2.2. Segmented Industry Analysis. According to the latest version of Industrial Classification of National Economy (GB/T 4754–2017) issued by the General Administration of Quality Supervision, Inspection, and Quarantine of the

| Index | Meaning | Situation | Specific significance |
|-------|---------|-----------|-----------------------|
| M     | Malmquist productivity index | $M > 1$ | Increased productivity |
|       |         | $M = 1$  | Constant productivity  |
|       |         | $M < 1$  | Decreased productivity |
| TC    | Transition degree of technical production boundary from $t$ to $t + 1$ | $TC > 1$ | Technological progress |
|       |         | $TC = 1$ | Technology unchanged  |
|       |         | $TC < 1$ | Technological decrease |
| EC    | Change degree of relative technical efficiency from $t$ to $t + 1$ | $EC > 1$ | Increase in technical efficiency |
|       |         | $EC = 1$ | Technical efficiency unchanged |
|       |         | $EC < 1$ | Decrease in technical efficiency |

Table 1: Specific significance of each index in the Malmquist index.

| City     | 2018 | 2019 | 2020 |
|----------|------|------|------|
| Wuhan    | 1.54 | 1.32 | 1.36 |
| Huangshi | 1.33 | 1.75 | 1.41 |
| Ezhou    | 0.40 | 0.42 | 0.40 |
| Xiaogan  | 0.47 | 0.54 | 0.55 |
| Xianning | 0.62 | 0.78 | 0.86 |
| Xiantao  | 0.61 | 1.10 | 1.08 |
| Tianmen  | 0.24 | 0.34 | 0.27 |
| Qianjiang| 0.50 | 0.41 | 0.35 |

Note. Missing data in Huanggang.

Table 2: Concentration level of talent elements in the Wuhan city circle, 2018–2020.

| City     | Year |        |        |        |
|----------|------|--------|--------|--------|
| Wuhan    | 2018 | 1.03   | 0.97   | 0.95   |
| Huangshi | 2018 | 1.52   | 1.44   | 1.48   |
| Ezhou    | 2018 | 0.93   | 0.99   | 1.10   |
| Xiaogan  | 2018 | 1.28   | 1.31   | 1.34   |
| Xianning | 2018 | 0.57   | 0.91   | 0.90   |
| Xiantao  | 2018 | 0.35   | 0.66   | 0.73   |
| Tianmen  | 2018 | 0.23   | 0.35   | 0.38   |
| Qianjiang| 2018 | 0.79   | 0.78   | 0.81   |

Note. Missing data in Huanggang.

Table 3: Concentration level of capital elements in the Wuhan city circle, 2018–2020.

| City     | 2018 | 2019 | 2020 |
|----------|------|------|------|
| Wuhan    | 1.03 | 0.97 | 0.95 |
| Huangshi | 1.52 | 1.44 | 1.48 |
| Ezhou    | 0.93 | 0.99 | 1.10 |
| Xiaogan  | 1.28 | 1.31 | 1.34 |
| Xianning | 0.57 | 0.91 | 0.90 |
| Xiantao  | 0.35 | 0.66 | 0.73 |
| Tianmen  | 0.23 | 0.35 | 0.38 |
| Qianjiang| 0.79 | 0.78 | 0.81 |

Note. Missing data in Huanggang.

Table 4: Calculation results of innovation performance of manufacturing industries in Wuhan, 2018–2020.

| Year | Index        |        |        |        |
|------|--------------|--------|--------|--------|
|      | Effch        | Techch | Pech   | Sech   |
| 2019 | 1.443        | 0.812  | 1.116  | 1.293  | 1.171  |
| 2020 | 0.511        | 2.000  | 0.684  | 0.747  | 1.022  |
| Mean | 0.859        | 1.274  | 0.873  | 0.983  | 1.094  |
People’s Republic of China and the National Standardization Administration of China, the manufacturing sector includes 31 major categories. However, due to incomplete data, leather, fur, feather and their products, and shoemaking industry, wood processing and wood, bamboo, rattan, palm, and grass products industry, chemical fiber manufacturing industry; metal products industry; machinery; and equipment repair industry will not be considered. Therefore, 27 manufacturing subsectors in Wuhan were selected as decision-making units, as follows: DMU1—agricultural and sideline food processing industry; DMU2—food manufacturing; DMU3—wine, beverage and refined tea manufacturing; DMU4—tobacco products industry; DMU5—textile industry; DMU6—textile and garment, and garment industry; DMU7—furniture manufacturing; DMU8—papermaking and paper products industry; DMU9—reproduction of printing and recording media; DMU10—cultural, educational, industrial, aesthetic, sports, and recreational goods manufacturing; DMU11—petroleum, coal, and other fuel processing industry; DMU12—chemical raw materials and chemical products manufacturing; DMU13—pharmaceutical manufacturing; DMU14—rubber and plastic products industry; DMU15—nonmetallic mineral products industry; DMU16—ferrous metal smelting and calendering processing industry; DMU17—nonferrous metal smelting and calendering processing industry; DMU18—metal products industry; DMU19—general equipment manufacturing; DMU20—special equipment manufacturing; DMU21—automotive manufacturing; DMU22—railway, marine, aerospace, and transport equipment industry; DMU23—electrical machinery and equipment manufacturing; DMU24—computer, communication, and other electronic equipment manufacturing; DMU25—instrumentation manufacturing; DMU26—other manufacturing; and DMU27—comprehensive utilization of waste resources. Similarly, the DEA-Malmquist index model was used to measure the innovation performance of 27 manufacturing subsectors in Wuhan. The results are shown in Table 5.

Table 5: Calculation results of innovation performance of 27 manufacturing segments in Wuhan, 2018–2020.

| DMU | Effch | Techch | Pech | Sech | Tfpch |
|-----|-------|--------|------|------|-------|
| DMU1 | 1.955 | 0.823  | 1.952 | 1.002 | 1.609 |
| DMU2 | 1.236 | 1.029  | 1.272 | 0.972 | 1.272 |
| DMU3 | 0.296 | 1.250  | 0.353 | 0.840 | 0.370 |
| DMU4 | 1.121 | 1.709  | 1.000 | 1.121 | 1.916 |
| DMU5 | 0.679 | 0.987  | 0.673 | 1.009 | 0.670 |
| DMU6 | 1.041 | 0.826  | 0.856 | 1.216 | 0.860 |
| DMU7 | 1.096 | 1.805  | 1.000 | 1.096 | 1.979 |
| DMU8 | 0.463 | 2.468  | 0.498 | 0.930 | 1.143 |
| DMU9 | 0.473 | 1.461  | 0.519 | 0.911 | 0.691 |
| DMU10 | 0.661 | 1.155  | 0.917 | 0.721 | 0.764 |
| DMU11 | 1.464 | 1.749  | 2.023 | 0.724 | 2.562 |
| DMU12 | 0.830 | 1.263  | 0.915 | 0.907 | 1.048 |
| DMU13 | 1.162 | 1.081  | 0.700 | 1.660 | 1.256 |
| DMU14 | 0.600 | 1.374  | 0.545 | 1.100 | 0.825 |
| DMU15 | 1.146 | 1.407  | 1.147 | 0.999 | 1.612 |
| DMU16 | 0.925 | 1.205  | 0.481 | 1.924 | 1.115 |
| DMU17 | 0.843 | 0.792  | 1.000 | 0.843 | 0.668 |
| DMU18 | 0.818 | 1.274  | 0.789 | 1.038 | 1.043 |
| DMU19 | 0.813 | 1.458  | 0.959 | 0.848 | 1.185 |
| DMU20 | 0.754 | 1.411  | 0.818 | 0.922 | 1.064 |
| DMU21 | 1.103 | 1.114  | 1.310 | 0.842 | 1.228 |
| DMU22 | 0.811 | 1.420  | 0.642 | 1.263 | 1.152 |
| DMU23 | 0.837 | 1.159  | 1.000 | 0.837 | 0.970 |
| DMU24 | 0.715 | 1.625  | 1.000 | 0.715 | 1.162 |
| DMU25 | 0.792 | 1.368  | 1.149 | 0.689 | 1.083 |
| DMU26 | 1.305 | 0.847  | 1.037 | 1.258 | 1.104 |
| DMU27 | 0.863 | 1.571  | 0.895 | 0.964 | 1.355 |

Mean 0.859 1.274 0.873 0.983 1.094

Comparing the total factor productivity value, it can be found that the technical efficiency value of many high-tech and high-value-added industries whose total factor productivity value was greater than 1 was less than 1, which indicates that the technical efficiency value is not a factor hindering the growth of the total factor productivity. There were only 5 industries with a technical progress value of less than 1, namely, DMU1, DMU5, DMU6, DMU17, and DMU26. Through comparison, it is found that the low innovation performance of DMU6 and DMU17 was mainly caused by the decrease in the value of technological progress.

4.3. Evaluation and Analysis of Manufacturing Innovation Performance in Wuhan City Circle. Due to the incomplete data of the five cities—Huangshi, Ezhou, Huanggang, Xiaogan, and Qianjiang, four cities—Wuhan, Xianning, Xiantao, and Tianshui are selected for further analysis. The DEA-BCC model is selected for calculation based on the input and output data from 2018 to 2020 using Deap2.1, and the innovation performance is comprehensively evaluated by Crste, Vrste, Scale, etc. The results are shown in Table 6.

Table 6 shows that the technical efficiency value of Wuhan’s innovation performance in 2018–2020 was less than 1, that is, technology invalid. The technological efficiency value of the innovation performance of Xianning,
Xiantao, and Tianmen was equal to 1, which is technology effective, indicating that the technological innovation performance of these three cities was better. In an economic sense, compared with other cities, the main reason why the technical efficiency value of Wuhan was less than 1 is the relative technical ineffectiveness caused by the low-scale efficiency value. Further research found that the biggest problem with manufacturing innovation was that it did not amplify the spillover effect of Wuhan’s manufacturing industry. In addition, the traditional industries in the manufacturing industry in the Wuhan city circle accounted for more than 70%, and the COVID-19 has adversely affected the investment in innovation[26]. Those two reasons directly affect the innovation performance of the manufacturing industry in the Wuhan city circle.

5. Conclusions and Implications

5.1. Conclusions. First, starting from the dimensions of technological efficiency, technological progress, scale efficiency, and total factor productivity, this paper conducts a longitudinal analysis of the innovation performance of Wuhan’s manufacturing industry and finds that technological progress has a positive impact on total factor productivity. Meanwhile, through comparison, it is found that there was an imbalance in the innovation ability of manufacturing enterprises in Wuhan. Traditional labor-intensive industries had a lower value of technological progress and a lower demand for innovation. The technological progress of knowledge-intensive high-tech and high-value-added industries was on the rise, and the level of innovation was generally high.

Second, after measuring the manufacturing innovation performance of the four cities in the Wuhan city circle from 2018 to 2020, it is found that there was no redundancy in its input and output, but because the technical efficiency value of Wuhan was less than 1, its technology was invalid, and the comprehensive efficiency and scale efficiency were the main reasons to cause the failure of its technological innovation. It can be seen from the calculation of scale efficiency that the result of scale efficiency was IRS (incremental); that is, with the continuous improvement of the economic development level in Wuhan, the enhancement of technological innovation capabilities can effectively improve the situation of insufficient technological innovation ability in Wuhan. However, since we only have the overall data of four cities and lack the relevant data of the Wuhan city circle as a whole, and the effectiveness of DEA is only relatively effective, it can be found that the innovation input in other cities except Wuhan was not high, and the innovation output was insufficient, yet the result was still valid. Therefore, the results can only be used for reference and cannot actually reflect the innovation performance of the manufacturing industry in the Wuhan city circle. We found that most of the manufacturing innovation capabilities in the Wuhan city circle were concentrated in Wuhan, and because of the epidemic, the low demand for technology and investment in the past two years have directly affected the innovation efficiency of the manufacturing industry.

Third, the construction of scientific and technological innovation databases is lagging behind. This article is based on the Hubei Statistical Yearbook and combines the statistical yearbooks and statistical bulletins of various places in the Wuhan city circle. However, we found that the variables included in the statistical yearbooks of different cities are not the same. Only the statistical yearbooks of Wuhan and Xiantao have complete data related to innovation in various manufacturing industries. While the yearbooks of some cities only have innovation input but no innovation output data, and even the yearbooks of most other cities only have industry-wide statistics. It shows that some cities did not pay enough attention to manufacturing innovation research, which leads to a lag in statistical work.

5.2. Policy Implications. First, the transformation of scientific and technological achievements needs to be strengthened and the marketization of scientific and technological achievements should be promoted. First of all, manufacturing enterprises can learn management experience from enterprises that are DEA effective, and can optimize their investment in R&D funds, equipment, and personnel and increase technological transformation. Secondly, manufacturing enterprises also need to pay attention to the market demand for innovative products when developing and innovating, attach importance to market-oriented innovative research and development activities, and avoid the situation where scientific and technological achievements cannot obtain corresponding shares in the market, which in turn leads to lower innovation output. Finally, the Wuhan city circle can make full use of the strong scientific and technological talents and technical achievement reserve resources of existing universities and scientific research institutions in Wuhan, combining it with its own production and sales capabilities to quickly enhance its independent innovation capabilities.
Second, the investment in technology research and development of manufacturing enterprises should be increased and allocated reasonably to improve the efficiency of the use of innovation resources. Although the impact of technological progress on innovation performance is positive from the perspective of Wuhan’s entire industry, there is still a certain gap compared with central cities in other urban circles. Promoting technological progress requires increased scientific and technological funding support. Hence, local governments could establish special funds to expand funding for technological innovation. Besides, through policies such as reducing taxes and reducing loan interest rates, governments can encourage the manufacturing enterprises in the Wuhan city circle to carry out independent innovation, and encourage financial institutions to support the innovative activities of manufacturing enterprises.

Third, the evaluation mechanism for scientific and technological talents shall be optimized, and the rational flow of talent shall be encouraged. At the enterprise level, it is necessary to pay attention to the investment of innovative talents, optimize the management mechanism of innovative talents, and improve the incentive and constraint mechanism. At the government level, it is urgent to establish a system to encourage the reasonable flow of innovative talents in the Wuhan city circle and attract innovative talents to go deep into manufacturing enterprises through joint cultivation and mutual utilization.

Fourth, the manufacturing industry in the Wuhan city circle requires coordinated development. As the central city of the Wuhan city circle, Wuhan is rich in technology, talents, and various infrastructure resources, and it is necessary to strengthen inter-regional manufacturing cooperation, enhance inter-regional synergy, and promote the rational circulation and sharing of inter-regional innovative resources. From the industrial level, the Wuhan city circle should rely on the industrial chain model to drive other cities with Wuhan as the core, establish multiple industrial chains, and reduce the redundancy of input resources. In addition, the Wuhan city circle should also take advantage of the large number of talents in Wuhan’s universities, strengthen the cooperation between universities and scientific research institutes, build an industry-university-research cooperation system, accelerate the upgrading of various industries in the manufacturing industry, and build a sustainable manufacturing innovation chain.

Fifth, the database construction needs to be strengthened. First of all, the various channels involved in the reporting of innovation input and innovation output data of various departments need to be thoroughly investigated, the timeliness of information update and utilization efficiency need to be analyzed, and the information barriers between different departments need to be broken down. At the national level, the flow of innovation elements and the dynamic detection network of manufacturing innovation capabilities need to be established, the incentive and restraint mechanism for information notification needs to be constructed, and the third-party evaluation needs to be carried out. Finally, big data analysis on the flow of innovation factors and manufacturing development needs to be strengthened.

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 there are no conflicts of interest regarding the publication of this article.

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