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Research Article

A Study on the Measurement and Influencing Factors of Innovation Governance Performance of Hubei Province in China Based on Technology Heterogeneity

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Exploring areas of innovation and development and promoting total factor productivity is a topic that is crucial to implementing innovation-driven strategies and building a modern economic system in the Hubei province in China. So, the aim of the research is to find a methodology for computing innovation performance and its influence factors in the Hubei region of China. Based on the existing efficiency measurement methods, this study measures the innovation efficiency performance and subsequently the innovation performance by using the optimized Färe-Primont index for a sample of 28 manufacturing industries in Hubei. A threshold regression model of multidimensional explanatory variables focusing on business performance, government support, industry openness, and synergic innovation is used to investigate the core factors that affect the improvement of innovation performance in Hubei's manufacturing industries. Results show that there is a significant "technological heterogeneity" in Hubei's manufacturing industries. Business performance plays a significant role in promoting the innovation performance of manufacturing industries, while the roles of industry development, government support, and synergic innovation on innovation performance change depending on the "technological characteristics" of industries.

1. Introduction

Accelerating the construction of the manufacturing powerhouse and increasing the industrial total factor productivity (TFP) are the key goals for the modern economic system proposed by China. The Hubei province, located in the centre of China, was called to persist in innovative leadership and prioritize efficiency while building a "strong manufacturing province." In this regard, the province should strive to explore a new structure for high-quality manufacturing innovation and development, maintaining TFP at its core. So, the analysis aims to find a methodology for measuring the TFP in the area of innovation governance and its influencing factors in the Hubei province of China so as to promote high-quality development.

In reality, as the vanguard of Hubei's regional economic development, the manufacturing industry is the leading and pillar industry of Hubei's provincial economic development, and it plays a pivotal role in realizing the aforementioned developmental strategy. Moreover, under the background of accelerating national economic transformation and strengthening "innovation drivers," innovation has become a core factor for improving the competitiveness of Hubei's manufacturing market and supporting the sustainable development of its industrial enterprises. Innovation is highly valued by companies across all industries. Statistics show that after the 11th Five-Year Plan of China, the R&D expenditure of large and medium-sized industrial enterprises in the Hubei province increased from CNY 3.860 billion in 2006 to CNY 107.722 billion in 2020, with an average annual growth rate of nearly 26.84%. In 2020, the number of people engaged in technological activities increased from 67,882 in 2006 to 167,797, with an average annual increase of nearly 6.67%. Considering these statistics, it can be predicted that high-input innovation will lead to a surge in innovation

output. For example, we may examine the number of patent grants, which reflects the innovation capability of the manufacturing industry accurately. In 2006, the number of patent applications for industrial enterprises in the Hubei province was 1,126, but it rose to 19,574, representing an increase of nearly 17.38 times over the 10-year period. A series of input-output data shows the crystallization of the effective outcomes of manufacturing innovation development in the Hubei province and a steady increase in the independent innovation capabilities of Hubei's manufacturing industry. However, behind the remarkable achievements, we should note that Hubei must not only focus on the orderly growth of innovation input and total innovation output but also emphasize issues related to innovation performance while "building a strong and innovative province." Particularly, Hubei should focus on the transformation and upgrading of manufacturing through the promotion of TFP because innovation performance is directly related to the sustainability of innovation investment, which indirectly impacts the market competitiveness of industrial enterprises and the innovation "enthusiasm" of industrial enterprises. By ensuring the improvement of innovation performance while maintaining the rapid growth of innovation investment and total innovation output, the Hubei province can gradually emerge as a "strong and innovative province" and offer robust technological support to realize the strategic goal of "constructing a pivot point and heading for the forefront."

2. Literature Review

The measurement of the innovation performance of industrial enterprises is divided into result performance and efficiency performance; additionally, the measurement of efficiency performance is conducive to the transformation of technological innovation activities in industrial enterprises from extensive to intensive development [1]. Existing studies have adopted three methods for efficiency measurement—parametric estimation, semiparametric estimation, and nonparametric estimation (see Figure 1). The fundamental idea of constructing a model is to maximize output, minimize cost, or maximize profit.

Every efficiency measurement method has certain adaptability and limitations. However, parametric estimation focuses on the selection and calculation of the production frontier and the influence of the residual correlation on the efficiency value caused by production frontier selection [7]. Although stochastic frontier estimation (SFA) can separate "noise items" from efficiency value calculations, it is difficult to process multi-input and multioutput industry-level data. The semiparametric method can overcome the shortcomings of the current parametric estimation method, but its application in existing literature is generally based on microdata demonstrations [6, 8, 9]; additionally, there is a lack of analysis based on "meso-level" industry data. However, the calculation of efficiency distance using nonparametric estimation is based entirely on the input-output relationship of the dataset, thus avoiding the impact of different forms of production function on the efficiency calculation. However, the nonparametric method is subject to constraints such as economic scale and input and output orientation. Based on previous studies [2–6, 10, 11], this study compares three types of efficiency measurement methods from various perspectives, as shown in Table 1.

In the research field of innovation performance, studies have mainly used three types of research methods to analyze China's industrial manufacturing innovation performance and its influencing factors from the perspective of input and output, two-stage innovation performance, and green innovation, by using regional industry macroeconomic data or survey data of Chinese industrial enterprises as samples, as shown in Table 2.

In summary, two shortcomings still remain in the current research on the innovation efficiency of Chinese industrial enterprises. First, the current research scale is mainly restricted to the national or regional level, and few studies have been conducted on industrial enterprises at the provincial scale. In fact, under the background of China's economic and social development that features strict administrative divisions, the scientificity and operability of the development pathways of innovation performance in the industrial sector at the national level are debatable. Second, the issue of heterogeneity should be taken into consideration. There are many studies on the heterogeneity of location, firm size, and enterprise ownership structure, but few focus on technological heterogeneity. Many types of industrial sectors exist and they exhibit significant variance in terms of technology dependence. For example, asset-intensive industries, such as ferrous metal smelting, are far less innovative than technology-intensive industries such as electronic equipment manufacturing. Therefore, the inclusion of technological heterogeneity factors in the research of factors affecting the innovation performance of industrial enterprises can strengthen the research conclusions and improve the accuracy of policy recommendations.

Based on the previous analysis, the Hubei province is considered to be in an important position in the development strategy of the Yangtze River Economic Belt, and the developmental foundation of its industrial sectors represents and advances the promotion of the national innovation strategies. Therefore, this study selected the manufacturing sector in the Hubei province as the research sample to conduct in-depth research on its innovation performance and influencing factors. The study is presented as follows: the first part presents the research background and literature review; the second part presents the theoretical framework for measuring the innovation efficiency performance of industrial enterprises, including the method design and construction of an indicator system; the third part presents an empirical study of the innovation performance of the manufacturing industry in the Hubei province; the fourth part analyzes the influencing factors of the innovation performance of the Hubei province; the fifth part offers a conclusion and policy recommendations.

3. Theoretical Framework

3.1. Method Design. The innovation efficiency of an industrial sector is different from that of a single enterprise. It

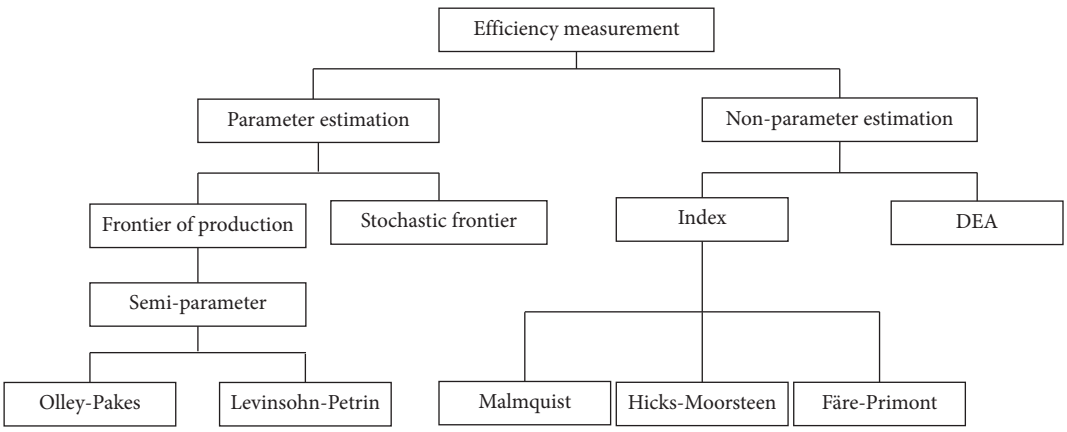

Figure 1: The category of efficiency. Note that the source is from Bosca et al. [2], Eberhardt [3], Grosskopf and Margaritis [4], See and Li [5], and Yang [6].

Table 1: Comparison of parameters of efficiency measurement methods.

Comparison parameters	Semi-parametric estimation	Parametric estimation		Semi-parametric estimation	
		Production frontier estimation	Stochastic frontier estimation	DEA	Index method
Production function	Requires predetermination	Requires predetermination	Requires predetermination	Unnecessary	Unnecessary
Best frontier	Not sensitive	Not sensitive	Not sensitive	Affects efficiency estimation	Sensitive
Sample size	Moderate	Moderate	Large sample	Small sample is feasible	Small sample is feasible
Multicollinearity of input indicators	May affect parametric estimation	May affect parametric estimation	May affect parametric estimation	No effect	No significant effect
Measurement error	Uncertain	Error less than DEA	Measurement error can be reduced by distribution assumptions	Highly sensitive	Impact exists
Statistical test	Usable	Usable	Usable	Usable	Unusable

Table 2: Descriptive analysis of the main literature on innovation efficiency and performance in China's industrial sector.

Source	Efficiency measurement method	Research interval	Research subjects	Innovation efficiency value	Influencing factors
Zhong et al. [12]	DEA	2004	Provincial manufacturing in China	Innovation efficiency: 0.476–1	
Song et al. [13]	DEA	2003–2008	Large and medium-sized industrial enterprises in China	Innovation efficiency: 0.005–1	Positive factors: Financial constraints, firm size, and regional factors Negative factors: Fixed assets
Zhou et al. [14]	DEA	1996–2018	Provincial industrial enterprises in China	Green innovation efficiency: 0.166–1	Positive factors: Government support for technology, government environmental protection, and technological awareness
Guan and chen [15]	Two-stage DEA	2002–2003	High-tech industry in China	Full efficiency: 0.253–1.0 R&D efficiency: 0.146–1.0	Positive factors: Business environment and industrial investment Negative factors: Government investment
Chiu et al. [16]	Two-stage DEA	2004–2007	China's two-digit high-tech industry	R&D efficiency: 0.162–1 Operational efficiency: 0.111–1	

Table 2: Continued.

Source	Efficiency measurement method	Research interval	Research subjects	Innovation efficiency value	Influencing factors
Xiao et al. [17]	Two-stage DEA	2005–2010	Large and medium-sized industrial enterprises in China	Overall innovation efficiency: 0.694	Factors affecting R&D efficiency: Firm size (positive) and number of scientists (negative) Factors affecting overall efficiency: Firm size (positive) and government support (negative)
Yu et al. [1]	Meta-frontier DEA	2001–2017	Large and medium-sized industrial enterprises in China	Average R&D efficiency: 0.683 Average green conversion efficiency of results: 0.656	Positive factors affecting R&D efficiency: Ownership structure, foreign investment, and technology trading environment Factors affecting the efficiency of results conversion: Technology trading environment (positive) and firm size and ownership structure (negative)
Dong and Wu [18]	SFA	1998–2018	Large and medium-sized industrial enterprises in China	Innovation efficiency: 0.3585–0.7122	Positive factors: Proportion of private economy and level of economic development Negative factors: Government R&D investment
Sun, Chen [19]	SFA	1999–2008	Large and medium-sized industrial enterprises in China	Average innovation efficiency: 0.4514	Positive factors: Open innovation systems, mature technology markets, intellectual property protection, and cooperation networks for innovation systems Negative factor: Government technology investment

measures the ratio of the industry's technological level under different conditions within the same period, giving the ratio of the TFP of innovation. TFP can be understood as the return of investment of industrial enterprise factors in the field of innovation, reflecting the technological level of industrial enterprises in the current period. Therefore, in order to measure the innovation efficiency of industrial sectors, it is necessary to formulate a method for calculating TFP that reflects the technological level of the overall industry. The construction of total input and output functions for industrial enterprise innovation is crucial for calculating the multi-input and multioutput innovation TFP. Obtaining the ratio of the previous functions gives the innovation TFP of the sector. We assume $x_{it} = (x_{1it}, \ldots, x_{kit})'$ and $q_{it} = (q_{1it}, \ldots, q_{kit})'$ by which the input and output vectors for sector i in period t are represented, respectively; thus, the TFP value of sector i in period t is

$$TFP_{it} = \frac{Q_{it}}{X_{it}}. \tag{1}$$

In the equation, $Q_{it} \equiv Q(q_{it})$ and $X_{it} \equiv X(x_{it})$ are the aggregate functions of the output and input vectors, respectively. The design of aggregate functions in the existing literature is mainly based on Shephard's distance functions, such as the Malmquist, Hick–Moorsteen, and Färe–Primont indices. Considering the comparability, decomposability, and transitivity of the innovation efficiency [8], this study selected the Färe–Primont index model to calculate the aggregate functions of the output and input vectors.

The innovation performance of the provincial industrial sector can be considered as the ratio of the current actual technological level of the industry and maximum technological level achievable under the constraint of the current technological level as follows:

$$\begin{aligned} E_{it} &= \frac{TFP_{it}}{TFP^*} \\ &= \frac{Q_{it}/X_{it}}{Q^*/X^*}. \end{aligned} \tag{2}$$

In the equation, Q^* and X^* are the total output and input amounts, respectively, needed to achieve the maximum value of technological value. Under input-oriented conditions (The main purpose of selecting an input-oriented efficiency performance calculation and decomposition is to effectively fulfill the "two-oriented societal" strategies of "resource conservation and environmental improvement."), the innovation efficiency value is decomposed into technological efficiency (ITE), scale efficiency (ISE), range efficiency (ISC), and mixed efficiency (IME) as follows:

$$ITE = \frac{\overline{X}_{it}}{X_{it}},$$
$$ISE = \frac{Q_{it}/\overline{X}_{it}}{\widetilde{Q}_{it}/\widetilde{X}_{it}},$$
$$ISC = \frac{\widetilde{Q}_{it}/\widetilde{X}_{it}}{Q_t^*/X_t^*},$$
$$IME = \frac{\widehat{X}}{\overline{X}_{it}}. \tag{3}$$

In these equations, $\overline{X}_{it}$ is the minimum amount of input that can be achieved when input kx_{it} produces output q_{it}. $\widetilde{Q}_{it}$ and $\widetilde{X}_{it}$ represent the total output and input that maximize the innovation efficiency value when the input and output vectors are λx_{it} and μq_{it}, respectively [20].

3.2. Indicator System

3.2.1. Output Indicators. The innovation output of industrial enterprises is mainly reflected in two aspects, namely, the technological value and economic value. The technological value represents the independent innovation ability of industrial enterprises, and it is an important embodiment of the sustainable development of industrial enterprises, while the economic value is the foothold of innovation investment in industrial enterprises and one of the characteristics of innovative behaviors in the form of enterprise organization. Referring to the principles in the available literature and data [1, 17, 18], the research team selected the number of invention patent applications (ZL) to represent the technological value of industrial enterprises and the sales revenue of new products (XS) to represent their economic value in the calculation of the innovation output vector q_{it}. Combining the two types of values in the same framework for research not only more comprehensively reflects the purpose of industrial enterprise innovation but also improves the current literature, which overemphasizes the economic value of industrial enterprise innovation in the study of their behavior and disregards patent output as an intermediate input (Current research is subject to the availability of data from subsectors and mainly applies economic value indicators to represent the output of innovation in industrial enterprises. It is also subject to research methods such as the two-stage DEA method, in which the output of innovation economic value is significantly higher than that of the technological value).

3.2.2. Input Indicators. In terms of innovation input in industrial enterprises, we referred to the selection of indicators in most studies [1, 14–17]. In terms of human resources input, this study selected the full-time equivalent of R&D personnel (RL), which is an internationally recognized indicator, based on the value chain of industrial enterprise innovation behavior. Human resources investment (FW) was represented by the number of technical personnel in industrial enterprises such that the indicator system of human resources input covers the overall innovative behaviors process of an industrial enterprise. Following the logic of the human resources indicators, R&D expenditure (JF) and new product development expenditure (KF) were selected as indicators of capital investment to match the production value chain of industrial enterprise's innovation behavior.

4. Research on the Measurement of Innovation Efficiency Performance of Industrial Enterprises in the Hubei Province

4.1. Research Subjects and Data Preprocessing. The research subjects of this study comprise 28 two-digit manufacturing industries under the jurisdiction of the Hubei province (As the plastic product and rubber product industries were combined in the third economic census, this study combined the data of the two industries in the years 2004, 2008, 2016, and 2020 to ensure the comparability of the data.). The main data sources were the survey data of the Hubei province in the four China Economic Censuses and the Hubei Statistical Yearbook for the years 2004, 2008, 2013, 2016, and 2020. Data on the capital stock was sourced from the Hubei Statistical Yearbook and the economic and statistical database of China National Knowledge Infrastructure (CNKI) (https://www.cnki.net).

In data preprocessing, price interference was to be eliminated. The deflator for the value indicators in the innovation input-output indicator system (e.g., new product sales revenue, R&D expenditure, and new product development funding) was taken from the ring price index of the ex-factory price index of industrial producers (The price index of the rubber and plastic product industries was replaced by the average annual price index of these industries.), classified by industry in the China Urban Life and Price Yearbook. Additionally, the lag produced by intellectual capital on output was taken into consideration, and the research team referred to the processing method in Hela et al. [21] by selecting the stock of R&D expenditure and new product development expenditure as the capital investment variable. The calculation method is the internationally accepted perpetual inventory method given as follows:

$$K_{it} = R_{it} + (1 - \delta)K_{i,t-1}. \tag{4}$$

In the equation, K_{it} represents the capital stock of sector i in period t, R_{it} is the current input of the indicator, and δ is the capital depreciation rate.

The base period for capital investment was set at 2004, and the calculation of the capital stock in the base period is presented as follows:

$$K_{i1} = R_{i0} + (1-\delta)R_{i,-1} + (1-\delta)^2 R_{i,-2} + \cdots = \sum_{s=0}^{\infty} R_{-s}(1-\delta)^s = \frac{R_{i1}}{g+\delta}. \quad (5)$$

In the equation, g is the average annual growth rate of the indicator input. Referring to the approach in Hall et al. [22] [23], we set g as 5% and δ as 15%.

Based on the previous equation, we used the SPSS software to perform a descriptive statistical analysis of each variable (see Table 3). As shown by the standard deviation, maximum value, minimum value, and kurtosis, significant sector differences were clearly seen in the innovation input and the output of Hubei's manufacturing industry and outliers.

4.2. Innovation Efficiency Performance of Industrial Enterprises. Based on the previous calculation method, DPIN3.0 was used to calculate the innovation efficiency performance, technological efficiency, scale efficiency, and range efficiency of various industries in the Hubei province.

4.2.1. Cross-Section Comparison Analysis. An analysis from a longitudinal perspective (As the time span of the data used in this study is somewhat long, we selected the calculation results of 2016 for the cross-sectional comparison to ensure the relevance and pragmatic of the conclusions of the analysis) shows that the overall innovation efficiency of manufacturing in the Hubei province is low. The average values of the industrial innovation efficiency and TFP are only 0.327 and 0.084, respectively, reflecting the low level of manufacturing technology and overall innovation efficiency in Hubei. An examination of specific subsectors shows that industries with a value below 0.2 include "textile, apparel, footwear, and headwear manufacturing," "petroleum processing, coking, and nuclear fuel processing," "chemical fiber manufacturing," "nonmetallic mineral product manufacturing," "specialized equipment manufacturing," and "communications equipment, computer, and other electronic equipment manufacturing." These manufacturing industries are considered to have extremely low innovation and efficiency. With a value of over 0.5, agricultural and sideline processing was the leading industry in Hubei in terms of innovation efficiency. The remaining 21 industries had a value between 0.2 and 0.5, implying a relatively underdeveloped innovation efficiency.

According to Färe–Primont's efficiency indicators, the reasons behind the low efficiency of manufacturing innovation in the Hubei province are mainly technological efficiency and range efficiency, rather than scale efficiency, as the ISE values of 28 industries are all 1. This indicates that the scale of innovation of the manufacturing industries in the Hubei province is at the frontier of optimal production, with prominent economies of scale.

The overall technological efficiency of industrial manufacturing in the Hubei province has been relatively good, and the average ITE value reached 0.768, indicating that the strategy of "innovation in Hubei" has achieved remarkable results in the construction of an innovative environment. This is especially evident in technology transactions and the conversion of technological achievements, which fulfill corporate needs and are market-oriented. The shared development model of research institutions and enterprises employed when jointly building innovative platforms has contributed to the prosperity of the technology transaction market and the industrialization of technological achievements. Industries with a technological efficiency of 1 were low-tech and medium-tech industries, including agricultural and sideline food processing, beverage manufacturing, tobacco manufacturing, furniture manufacturing, and paper and paper product manufacturing, except for pharmaceutical manufacturing, printing and recording media reproduction, educational sporting goods manufacturing, rubber and plastic product manufacturing, ferrous metal smelting and rolling processing, nonferrous metal smelting and rolling processing, and transportation equipment manufacturing. This illustrates that the industries that benefit most from the construction and improvement of the technology transaction market system in Hubei are traditional manufacturing industries rather than high-tech industries. This is also demonstrated by the technological efficiency value of the communications equipment, computers, and other electronic equipment manufacturing industry, which is only 0.421.

The research team believed that range efficiency is the main factor lowering the efficiency of the industrial manufacturing innovation in Hubei. The average efficiency value was only 0.555. Particularly, the following industries had an ISC value lower than 0.3 and were considered low-range-efficiency manufacturing industries: food production, paper and paper product manufacturing, chemical fiber manufacturing, nonmetallic mineral product manufacturing, and special equipment manufacturing. The following industries had an ISC value greater than 0.6 and were considered high-range-efficiency manufacturing industries: "agricultural and sideline food processing," "tobacco manufacturing," "printing and recorded media reproduction," "educational sporting goods manufacturing," "petroleum processing, coking, and nuclear fuel processing," "chemical raw material and product manufacturing," "pharmaceutical manufacturing," "general equipment manufacturing," "transportation equipment manufacturing," and "manufacturing of instruments and other machinery and equipment for cultural and office use." The remaining 13 industries had an ISC value between 0.2 and 0.6 and were considered to have a midrange to low-range efficiency. By analyzing the correlations between ISC and E and ITE, we found that the Spearman's correlation

Table 3: The description of variables.

Variables	ZL	XS	RL	FW	JF	KF
Means	252.65	7594.30	1810.82	1456.88	4704.57	4939.42
Standard errors	490.07	1992.80	3070.49	2421.06	1081.83	1127.30
Skewness	3.56	5.57	2.95	3.11	3.83	3.85
Kurtosis	15.36	36.93	9.97	11.13	15.52	16.10
Min	0.00	0.00	0.00	0.00	0.00	0.00
Max	3088	15291.75	17482.00	14022.00	58782.51	66489.83

coefficient of ISC and the other two were 0.595 and 0.755, respectively, both of which passed the significance test at the 1% level. This demonstrates that, in the context of synergy development among industries, the possibility of knowledge spillover is higher in high-tech industries, thereby broadening their range of technological activities and increasing industrial synergy. Increasing the level of industrial synergy will further expand the potential demand for their technological achievements and technological markets, helping them to enhance the scope and efficiency of technological activities and forming positive interactions.

4.2.2. Sequence Comparison Analysis. From a dynamic perspective, the value of only 5 of the 28 manufacturing industries in Hubei maintained an increase: "pharmaceutical manufacturing," "transportation equipment manufacturing," "electrical machinery and equipment manufacturing," "communications equipment," "computer and other electronic equipment manufacturing," and "manufacturing of instruments and other machinery and equipment for cultural and office use," while the rest of the industries displayed a volatile trend. Particularly, industries that showed characteristics of a "concave" shape include the following: "agricultural and sideline food processing," "food manufacturing," "tobacco products," "textile and clothing, footwear, and headwear manufacturing," "printing and recorded media reproduction," and "educational sporting goods manufacturing." This also shows that the deterioration of the economic environment has a greater impact on the technological level and innovation efficiency of the light textile manufacturing industry in Hubei. This is probably because of the low technological requirements in current light textile products, and hence the R&D intensity is relatively low in that industry. When there is insufficient external demand, an industry often responds to the crisis by reducing production, which further reduces investment in product innovation. Therefore, the industrial innovation efficiency in Hubei has witnessed a further decline.

In terms of technological efficiency, the dominant industries are furniture manufacturing and ferrous metal smelting and rolling processing. Their technological efficiency values were 1.0 for 4 years. Industries showing an increasing trend include the following: "tobacco product manufacturing," "chemical raw materials and chemical manufacturing," "pharmaceutical manufacturing," "rubber and plastic product manufacturing," "non-metallic mineral product manufacturing," "non-ferrous metal smelting and rolling processing," and "manufacturing of instruments and other machinery and equipment for cultural and office use." The value of 17 industries declined first and subsequently increased, indicating the effectiveness of the efforts and significant achievements made by Hubei in the continuous promotion and improvement of technology transactions and technological achievement transformation since the 12th Five-Year Plan.

In terms of range efficiency, the following industries showed an increasing trend: "printing and recorded media reproduction," "petroleum processing, coking and nuclear fuel processing," "general equipment manufacturing," "transportation equipment manufacturing," and "manufacturing of instruments and other machinery and equipment for cultural and office use." Only "textile and clothing, footwear, "headwear manufacturing" and "rubber and plastic product manufacturing" showed a decreasing trend. Except for "agricultural and sideline food processing," the other 19 industries with fluctuating values first increased subsequently declined, depicting a "convex shape." This indicates that, although the technological specialization of the manufacturing industries in Hubei has increased over the past 5 years, innovation cooperation and technological relevance are weakening, and the synergy development of innovation value chains is insufficient. This has resulted in the narrowing of benefits that are expected to emerge from technological achievements and a negative impact on industrial synergy and the improvement of range efficiency. In fact, by using R&D expenditure as a calculation indicator and Theil's entropy index [23], which measures the level of input diversification, the research team found that the diversification index of the Hubei province in 2004, 2008, 2013, 2016 and 2020 was 0.579, 0.638, 0.825, 0.833 and 0.851, respectively, indicating an increase in the level of specialization. This result confirms the study's viewpoint.

5. Analysis of Factors Affecting the Innovation Performance of Industrial Manufacturing in the Hubei Province

The aforementioned results demonstrate that the overall TFP of the 28 industries in Hubei has been low. The low level of innovation performance is transmitted to the market competitiveness of the industry through two channels—product innovation cost and product innovation technology. Ultimately, this will affect the sustainable development of the manufacturing industries in Hubei and the implementation effects of Hubei's strategies for economic and social transformation and upgrading. Therefore, finding the core factors

affecting the innovation performance of manufacturing in Hubei and the scientific pathways to improve it will help promote the implementation of the "Innovation in Hubei" strategy. This has important practical significance and policy implications and is the focus of this section.

5.1. Theoretical Hypotheses. In fact, from a regional viewpoint, the existing literature analyzes the main factors affecting manufacturing innovation performance from the perspectives of governments, markets, locations, and policies [13–17]. However, as the research subjects of this study are two-digit manufacturing industries within the province, the macro environment to which they belong is not much different (Since current public records do not provide complete macro-environmental data based on the differentiation of industries (e.g., the impact of industrial policies), this study does not consider control variables in subsequent model designs). Thus, it is necessary to analyze the factors influencing its innovation performance by referring to the internal characteristics of the industry.

5.1.1. Industry Business Performance. Business performance is the most important indicator to assess the industrial development level. Often, business performance is closely related to the innovation performance of industrial enterprises. First, from the perspective of products, the reason behind the superior performance of industrial enterprises is that their industrial products have strong market competitiveness; additionally, the innovative technologies in products manufactured by these enterprises are one of the most crucial factors affecting market competitiveness. For example, Huawei, the leading company in communications equipment manufacturing, has acquired 38,825 patents. Moreover, companies with better business performance tend to focus more on innovation and are willing to utilize more resources for innovation. The previous example can be employed to show that Huawei invests over 10% of its sales revenue in R&D every year, and more than 45% of the firm's employees are engaged in innovation, research, and development. Second, from an organizational perspective, companies with better business performance tend to have better organizational efficiency, which includes innovative organizational activities. Based on this, we propose hypothesis 1.

> Hypothesis 1: There is a positive relationship between business performance and innovation performance. Improving business performance of the manufacturing industries in Hubei contributes to the improvement of the innovation performance of these industries.

5.1.2. Government Support. Government support reflects the extent to which the government concerns the industry, inherently reflecting the status of the industry in the regional economy. The study of the relationship between government support and innovation performance is one of the hot topics of studies on innovation. Most of the existing literature s [13–19] believes that government support produces a "bumping-down effect." As the cost of using government funds is low and the purpose and assessment of innovation may be ambiguous, there may be idle resources or excessive consumption of resources, rendering government support unconstructive for the improvement of innovation performance. However, the arguments in the existing literature are mainly based on empirical research at the regional level, and very few examine the causal relationship between the two from an industry level. Regional-level research often focuses on regional heterogeneity factors (such as the division of the eastern and central-western regions) but disregards the bias that industry differences bring to the conclusions of the study. Research on the provincial scale should emphasize the impact of "meso-level" differences on innovation performance because regional differences are more manifested in the differences in an enterprise's external environment, but industry differences reflect the internal structural characteristics of the enterprise. Although the main drivers and motivation of innovation are enterprises and market demand, and government support may disrupt the market rules in Hubei, the economic development of Hubei is considered average in China. The pressure on enterprises from market competition is relatively high. Government support has helped alleviate the problem of insufficient investment in innovation due to operational pressures, thereby enhancing innovation momentum and market competitiveness of these enterprises. As such, we propose hypothesis 2:

> Hypothesis 2: There is a positive correlation between government support and innovation performance. Current government support can help improve the innovation performance of the manufacturing industry in Hubei.

5.1.3. Industry Openness. The openness of an industry reflects its level of external communication, communication, and cooperation. There is a debate about the impact of industry openness on innovation performance. First, open industries can obtain more innovative resources and information externally, and knowledge exchange is more likely to produce synergies, shorten innovation cycles, lead to key technologies, share innovation costs, reduce innovation risks, and enhance the motivation of innovation [24]. Therefore, Harun et al. [25] and Junnia et al. [26] both believe that an improvement in openness has positively contributed to the improvement of industry innovation performance. Second, the current industry development shows characteristics of "basic market openness, limited capital openness, and moderate technology openness," limiting the influence of innovation spillover in the process of opening up the industry. This leads to uncertainties in the promotion of innovation performance such as the impact of environmental dynamics [27]. In summary, considering the position of Hubei's manufacturing industries in the national industrial division of labor, it can be stated that manufacturing is more reliant on the role of producers; thus, the opening up of industries may lead to a further transfer of

innovation functions away from Hubei. Based on this, we propose hypothesis 3.

> Hypothesis 3: There is a negative correlation between industry openness and innovation performance. Improving the openness of manufacturing in Hubei leads to the deterioration of innovation performance.

5.1.4. Synergic Innovation. Synergic innovation is measured by the innovative organization methods of an industry. It is a new technological innovation paradigm [28] guided and institutionally arranged by the collective national will to encourage enterprises, universities, and research institutions to take advantage of their respective capabilities, integrate complementary resources, and accelerate the application and industrialization of technologies. The application and promotion of the synergic innovation paradigm can break through the barriers between the innovation subjects and fully release the vitality of innovation elements, including talent, capital, information, and technology to achieve deeper collaboration. Haider and Mishra [29] illustrated the positive effect of the synergy of various innovation subjects on the promotion of regional innovation performance from a geographical perspective. The purpose of building synergic innovation for industries is to improve their ability to innovate and improve innovation performance. Thus, we propose hypothesis 4.

> Hypothesis 4: Synergic innovation has a positive effect on innovation performance. Hence, strengthening collaborative innovation helps improve the innovation performance of manufacturing in Hubei.

5.2. Variable Design and Measurement Analysis Methods

5.2.1. Variable Measurement. Based on the theoretical hypotheses above, we constructed the relevant variables needed for this study by considering the availability of data and the economic significance of the data indicators.

(1) Business Performance (HYJX). The measurement of industry performance mainly includes indicators such as income from principal business activities and the operating profit. However, operating profit includes investment income, and the sources of investment income include real estate investment and investment in securities, which may not be related to the research topic of innovation performance. To improve the accuracy of our research conclusions and overcome the differences in business performance caused by scaling factors, we selected per capita income from principal business activities among industry practitioners as the indicator to measure business performance (The processing approach and data sources in Section 3 were used to deflate the indicators for income from principal business activities.).

(2) Government Support (ZFZC). Government support is offered through two channels—financial support and policy support. Since policy support is difficult to quantify directly, we measured government support using the amount of financial support. Government financial support mainly includes direct investment and indirect subsidies for innovation activities. Therefore, the proportion of government funds in the total amount of technology fundraising was selected as the measure of government support.

(3) Industry Openness (HYKF). Existing studies mainly analyze the measurement of openness from two aspects: export [30] and foreign investment [31]. In reality, from the perspective of industries, exports reflect the market competitiveness of an industry. The openness of capital is the most direct indicator of industry openness. Therefore, the ratio of capital from Hong Kong, Macao, and Taiwan, as well as foreign capital, to the industry's total paid-up capital is used to measure industry openness.

(4) Synergic Innovation (XTCX). Referring to the relevant studies [27–29] and considering that an industry's synergic innovation performance is the integration of production, learning, and research, this study selected the proportion of expenditure on research and higher institutions (included in technological activity funding) in the industry's external R&D expenditure to measure synergy innovation.

5.2.2. Model Formulation and Estimation. This study focuses on the "meso-level" of industries and considers the significant differences among industries in terms of dependence on technology. In accordance with "Moore's Law," high-tech industries, such as "communication equipment, computer and other electronic equipment manufacturing," and "manufacturing of instruments and other machinery and equipment for cultural and office use," have a technology life cycle that is equal to or less than 18 months. In contrast, the emergence of innovative technologies in traditional manufacturing industries, such as smelting and paper and paper product manufacturing, often takes 10 years or even longer. The variance in the level of reliance on technology across industries is defined as the technological heterogeneity of industries. In mathematical terms, this technological heterogeneity may result in heteroskedasticity in the measurement model. Practically, differences in the level of dependence on technology may lead to differences in the influencing factors of innovation performance. For example, industries with strong technology dependence may need additional innovation support in the form of "external expertise" due to market competition; hence, it can be stated that synergic innovation has a greater impact on the innovation performance of these industries. Therefore, this study introduced a non-linear panel threshold model to analyze the influencing factors of manufacturing innovation performance in Hubei to overcome the technological heterogeneity among industries.

The non-linear panel threshold regression model can capture the non-linear threshold characteristics produced by structural mutations in the economic system and can determine the threshold value by automatically identifying the sample data. It also possesses the effective characteristics of

the general panel data model [32]. Additionally, the existing literature focuses on analyzing whether there is a "threshold effect" between a single explanatory variable and an explained variable; however, there is less focus on analyzing the "threshold effect" between multiple explanatory variables and the explained variable. In this study, the technological heterogeneity of the threshold variable is an attribute of industry characteristics and has a certain correlation with the four explanatory variables. Therefore, this study refers to the modeling approach in Sophie et al. [33]. In constructing a regression based on the multi-dimensional threshold effect of explanatory variables:

$$E_{it} = \mu_i + \beta_i^{1'} X_{it} I(\gamma < \widehat{\gamma}) + \beta_i^{2'} X_{it} I(\gamma \geq \widehat{\gamma}) + \xi_{it.} \tag{6}$$

In this equation, $X_{it} = (HYJX_{it}, ZFZC_{it}, HYKF_{it}, XTCX_{it})'$, i and t represent industry and time, respectively. $I(\cdot)$ is the indicator function, γ is the estimated threshold value (The R&D intensity is used as the threshold variable γ. Thus, the value of "R&D Input/Industry GDP" is used to represent the technical heterogeneity of the industry.) and $\widehat{\gamma}$ is the optimal threshold value. $\beta_i^{1'}, \beta_i^{2'} = (\beta_{1i}, \beta_{2i}, \beta_{3i}, \beta_{4i})'$ is the estimated parameter, and ξ_{it} is the stochastic error term adhering to $\xi_{it} \sim iid(0, \sigma^2)$.

Concerning the estimation methods, we referred to the method adopted in Hansen [34] and applied the following steps:

First, taking the average of (6) over the time index t produces the following equation:

$$\overline{E}_i = \mu_i + \beta_i' \overline{X}_i I(\gamma) + \overline{\xi}_i, \tag{7}$$

where

$$\overline{E}_i = \frac{1}{T} \sum_{t=1}^{T} E_{it,}$$

$$\overline{\xi}_i = \frac{1}{T} \sum_{t=1}^{T} \xi_{it},$$

$$\overline{X}_i I(\gamma) = \frac{1}{T} \sum_{t=1}^{T} X_{it} I(\gamma) = \left(\frac{1}{T} \sum_{t=1}^{T} X_{it} I(\gamma < \widehat{\gamma}) \frac{1}{T} \sum_{t=1}^{T} X_{it} I(\gamma \geq \widehat{\gamma}) \right). \tag{8}$$

Then the difference between Equations (6) and (7) yields the model.

$$E_{it}^* = \beta_i' X_{it}^* I(\gamma) + \xi_{it}^*, \tag{9}$$

where

$$\begin{aligned} E_{it}^* &= E_{it} - \overline{E}_i, \\ X_{it}^* &= X_{it} - \overline{X}_i, \\ \xi_{it}^* &= \xi_{it} - \overline{\xi}_i. \end{aligned} \tag{10}$$

Subsequently, an ordinary least squares (OLS) estimation was performed on model (9) to obtain the estimated coefficient $\widehat{\beta}_i(\gamma)$ and the sum of residuals $\mathrm{SSE}(\gamma)$.

Finally, based on Arg $\min_\gamma \mathrm{SSE}(\gamma)$, we obtained the threshold value $\widehat{\gamma}$ to partition the sample group to estimate the correlation coefficients of the corresponding group, $\widehat{\beta}_i^1(\gamma)$ and $\widehat{\beta}_i^2(\gamma)$.

To estimate the determined threshold, a hypothesis test of the threshold regression model is required:

First, we verified whether the threshold effect is significant. The null hypothesis is H_0: $\beta_i^1 = \beta_i^2$ and the alternative hypothesis is H_1: $\beta_i^1 \neq \beta_i^2$; hence, the corresponding statistic is:

$$F_1 = \frac{\mathrm{SSE}_0 - \mathrm{SSE}_1(\widehat{\gamma})}{\widehat{\sigma}^2}. \tag{11}$$

In this equation, SSE_0 is the sum of squared residuals of the linear model under the condition of H_0. $\mathrm{SSE}_1(\widehat{\gamma})$ and $\widehat{\sigma}^2$ represent the residual squared sum and residual variance of the threshold regression model, respectively. Due to the uncertainty of the threshold value $\widehat{\gamma}$, F_1 does not fit the standard distribution. Hansen [34] used Bootstrap sampling to simulate the progressive distribution and obtained the progressive effective probability value p. When $F_1 < p$, the threshold effect is not significant.

Second, we verified whether the estimated threshold value is equal to the true value. The null hypothesis is H_0: $\widehat{\gamma} = \gamma_0$, and the alternative hypothesis is H_1: $\widehat{\gamma} \neq \gamma_0$; hence, the corresponding statistic is:

$$\mathrm{LR} = \frac{\mathrm{SSE}_1(\gamma_0) - \mathrm{SSE}_1(\widehat{\gamma})}{\widehat{\sigma}^2}. \tag{12}$$

Although the statistical value LR does not fit the standard distribution, the null hypothesis is rejected under the condition of the significance level τ when $\mathrm{LR} > -2\ln(1 - \sqrt{1-\tau})$.

5.3. Empirical Results and Analysis

5.3.1. Stationary Test. To prevent the occurrence of a "pseudo-regression," this study begins by testing the "stationary" of the variables by adopting the HT test (In this study, the sample data T are relatively small and have a long time span. To avoid not having a solution, the HT test was selected without considering the individual intercept and trend terms). Results are shown in Table 4.

Table 4 shows that each variable rejects the null hypothesis with a unit root, indicating that the existing variables are stationary sequences, and hence regression analysis can be performed on them.

5.3.2. Traditional Panel Data Model Estimation. To facilitate a comparative analysis, this study initially investigates the factors affecting the improvement of manufacturing performance in Hubei, without considering the threshold variables. Results are shown in Table 5.

As the Hausman test was significant at the 5% level in the ordinary panel model estimation, the fixed effect model was selected. The estimation results show that the business performance of industries has a significant positive effect on the improvement of manufacturing innovation performance in Hubei, while the level of industry openness has a significant negative effect, indicating that hypotheses 1 and 3 are valid.

Table 4: Test of units.

Varabiles	TFPE	HYJX	ZFZC	HYKF	XTCX	ITE
Test of HT	−12.910*** (0.000)	−10.480*** (0.000)	−41.099*** (0.000)	−3.906*** (0.000)	−13.340*** (0.000)	−3.554*** (0.002)

(***, **, and * represent the significance of 0.01, 0.05 and 0.1).

Table 5: The results of model estimation.

	Panel model		The threshold model of mutli-dimension independent variables			
			$\gamma < 0.0255$		$\gamma \geq 0.0255$	
	β_i	t	β_i^1	t	β_i^2	t
HYJX	0.1040***	3.135	0.0166***	3.591	0.1083***	7.897
ZFZC	−0.1781	−0.2611	0.0832*	1.345	−0.4527**	1.669
HYKF	−1.051**	−2.226	−1.0191***	14.343	−0.0604	1.105
XTCX	0.0091	0.2142	−0.0321**	1.987	0.1786***	20.77
R	2.690					
Hausman	12.59**					
Confidence interval				$\gamma = [0.0176\ 0.0347]$		
F				13.65***		
bootstrap				300		
Trimming				≥ 10%		

(***, **, and * represent the significance of 0.01, 0.05 and 0.1).

5.3.3. Threshold Model Estimation of Multi-Dimensional Explanatory Variables. According to the research approach above, this study uses the Bootstrap method to repeat the sampling 300 times; the estimation led to an F value of 13.65, which passes the 1% significance test. Thus, the assumption that the equation is a linear model is rejected.

Second, the estimated threshold for technological heterogeneity is 0.0255 (To avoid having too few samples in a given group interval, this study referred to the approach [33] by disregarding sample values lower than the 10% quantile or greater than the 90% quantile in determining the value of $\hat{\gamma}$), and its confidence interval at the 90% confidence level is [0.0176 0.0347]. Compared to the statistics of China's urban R&D intensity in 2016, 0.0255 ranked 14th among the key R&D cities (Data source: https://finance.sina.com.cn/roll/2017-09-04/doc-ifykpuui0996404.shtml), exceeding the average national R&D intensity in 2016 (0.0211), indicating that the threshold has credibility.

Finally, based on the analysis of regional results, this study divided the research sample into two categories: "strong R&D industry" and "weak R&D industry."

(1) First, the sample distribution's analysis diagram shows that the R&D intensity of most sectors in Hubei's manufacturing industry is increasing, which is consistent with the environment of technological and economic development in China and Hubei in the last decade. A series of national and provincial economic development strategies such as the "innovation-driven strategy" and "Five Hubeis" have significantly enhanced the awareness of enterprise innovation and promoted enterprise investment in innovation. Second, considering the limit of $\gamma = 0.0255$, the only "strong R&D industry" before 2008 was "communications equipment and computer and other electronic equipment manufacturing," while the rest of the industries did not exceed this threshold. After the financial crisis of 2008, 75% of the manufacturing industries in Hubei became "strong R&D industries." Only the following three industries remained in the "weak R&D industry" group: textile and apparel, footwear, "headwear manufacturing," "leather, fur, feather (velvet), and related product manufacturing," and "furniture manufacturing." However, they are not the dominant industries in Hubei, and they are subordinate to the entire industrial chain, mainly focusing on processing and OEM. This may be the reason behind their low enthusiasm for R&D investment. Particularly, R&D investment in the furniture manufacturing industry in 2020 was almost zero.

(2) As the industry heterogeneity factor of "R&D intensity" was considered in the analysis of influencing factors, the estimation results of the model were different from the traditional panel model estimation. Practically, industry performance is the most critical factor for improving innovation performance in manufacturing. Regardless of whether it is a strong or weak R&D industry, improving the business performance of the industry will significantly promote the improvement of its innovation performance. Based on the analysis of business management, innovative behavior is an essential part

of business management. Business performance that is detached from innovation performance is inevitably unsustainable because the weight of innovation performance in product competitiveness will become increasingly important. For instance, the electronic information industry was integrated into the global value chain earlier and has stood out in the global "red ocean" competition. Thus, the innovation performance of Hubei's electronic information industry has significant advantages over other industries [35]. This confirms hypothesis 1 of this study.

Compared to business performance, government support for improving the manufacturing performance in Hubei has significant differences in terms of "R&D intensity." To a certain extent, government support helps improve the innovation performance of industries in the "weak R&D intensity" group, while, for industries that have a strong R&D intensity, government support significantly inhibits the improvement of industry innovation performance. Hence, there are certain preconditions for validating hypothesis 2 in this study. In reality, when an industry has "weak R&D intensity," its participants may lack the subjective motivation for innovation investment or the prerequisites for increasing innovation resources. In this scenario, the industry needs the government's guidance to increase the "enthusiasm" and investment scale of innovation investment by government purchasing, tax incentives, or even direct investment. Unlike the law of diminishing returns to scale, the scaling effect of innovation investment is relatively dominant, thereby improving innovation performance. When the industry R&D intensity is greater than 0.0255, government support may produce a "crowding effect," which would not be conducive to the improvement of industry innovation performance. This finding is basically consistent with most conclusions in previous studies, and will not be elaborated here.

Concerning industry openness, hypothesis 3 is validated. However, with the improvement of the R&D intensity in a given industry, the negative impact of the opening up of an industry on the innovation performance of manufacturing in Hubei changes from being "significant" to "not significant." This change can be understood as the promotion of the leadership position of Hubei's manufacturing in external collaboration as a result of the improvement of innovation capability. Due to the inevitable positive correlation between R&D intensity and innovation capability, when the industry R&D intensity is low, and the industry innovation ability is not high, the knowledge spillover generated by foreign capital introduction limits the promotion effect on industry innovation. Foreign investment may also hinder the improvement of manufacturing innovation performance through market forces and technological monopolization, making it difficult for industries to successfully climb the value chain [36]. This is especially evident in Hubei's textile, nonferrous metal, and other traditional industries. As most enterprises are still focusing on the initial stage of raw materials processing, few have reached the "R&D" and "sales" stages in the smile curve, and thus their competitiveness is not strong (The main points were extracted from https://www.stats-hb.gov.cn/tjbs/fztjbs/112079.htm). An industry's innovation ability increases with the strengthening of R&D intensity, and the absorption capacity of innovation spillovers is improved. To a certain extent, the industry can be opened to the outside world through specific collaborative targets and models that are conducive to innovation spillovers. Therefore, among "strong R&D intensity" industries, the negative effect of the opening up of industries on innovation performance would be no longer significant.

The impact of synergic innovation on the innovation performance of manufacturing in Hubei also shows heterogeneity in terms of "R&D intensity." For manufacturing industries with a "weak R&D intensity," synergic innovation significantly inhibits innovation performance. However, deepening synergic innovation is effective for improving innovation performance among manufacturing industries in the "strong R&D intensity" group. This is somewhat different from the major research conclusions of the existing literature [29–36]. The research team believes that the reason for the difference is similar to the "threshold effect" of the opening up of industries on the improvement of innovation performance. The difference in the absorption capacity of synergic innovation spillovers may be the main reason behind this phenomenon. For manufacturing industries with "strong R&D intensity," developing synergic innovation is an effective supplement for innovative development as it produces a "$1 + 1 > 2$" multiplier effect. For those in the "weak R&D intensity" category, deepening synergic innovation may result in discoordination with targeted synergy organizations due to the relatively weak demand for innovation drivers or feeble accumulation of innovation. If there is a failure to match technological capabilities, then it may be difficult to achieve technological the expected technological results.

(3) Compared to the ordinary panel estimation model, the "threshold regression" model not only confirms the conclusion of hypothesis 1, similar to the above analysis, but also conditionally validates hypotheses 2, 3, and 4. In fact, it is even better than the ordinary panel estimation model in terms of the significance of coefficients, indicating that the use of the "threshold regression model" can overcome the problem of sample heterogeneity in

the manufacturing industry. The results obtained by the model estimation are more scientific and realistic.

6. Conclusion and Policy Suggestions

This study adopted the Färe-Primont index to measure the innovation performance of 28 industrial manufacturing industries in Hubei. By constructing a threshold regression model of multi-dimensional explanatory variables, it demonstrated the impact of business performance, government support, industry openness, and synergic innovation on the main factors affecting the improvement of innovation performance in Hubei. The conclusions are as follows. First, although the overall innovation input and output growth momentum of Hubei's manufacturing industries have been significant since the beginning of the new century, the innovation efficiency and the TFP are still low, indicating that the innovation development model of the manufacturing industries in Hubei is still driven by resources, and the technology-driven forces remain relatively insufficient. Second, the decomposition of TFP illustrates that the synergic development of the innovation value chain of Hubei's manufacturing industries is not high; this has resulted in a weak spillover effect of technological achievements and thereby affected the enhancement of industrial synergy and range efficiency. Third, there is a significant "technological heterogeneity" among the manufacturing industries in Hubei and its technological threshold (R&D intensity) is 0.0255. Finally, among the factors affecting the improvement of manufacturing innovation performance in Hubei, business performance has a significant positive correlation with the growth of innovation performance, industry openness only has a significant negative effect on industries with an R&D intensity below the threshold, while government support and synergic innovation have opposite significant effects on industries that belong to either of the threshold intervals.

Focusing on the new ideas of driving innovation and development in Hubei's manufacturing industries, and considering the results above, this study proposes the following three policy recommendations:

(1) Enterprises should persist under capital and market leadership and effectively improve business performance. The most noticeable difference between manufacturing and other industries is that capital investment is large and the proportion of fixed assets is high. Therefore, manufacturing enterprises in Hubei should strengthen business management by focusing on capital and establish and improve their corporate governance structures and incentive and restraint mechanisms in order to improve business performance. Enterprises should follow the laws of the market economy, optimize product structures, improve the technological content of products, and strengthen their core businesses. This would allow enterprises to obtain greater credit support from financial institutions and improve their operational leverage. Additionally, enterprises should strengthen the management of funds, calculate the cost of capital, accelerate the turnover of working capital, reduce the usage of fixed assets, and improve the efficiency of capital use. Furthermore, they should not only enhance "internal strengths" but also focus on the market and strengthen the matching between supply and demand. Manufacturing companies should focus on both supply and demand simultaneously; make full use of "digital tools" to find a supply and demand matching platform; and guide the existing technology, talent, and capital in the direction of social demand. By tapping into potential markets, enterprises can activate the guiding effects of the demand side on the supply side.

(2) The government should further standardize direct subsidies provided for the innovation of manufacturing enterprises, strengthen its supervision functions, and create a desirable environment for innovation and development of the manufacturing industry. In fact, after 2013, the R&D intensity of most manufacturing industries in Hubei exceeded the "threshold value" of 0.0255, indicating that the most important requirement for the innovation and development of Hubei's manufacturing industries was to enhance the "subjective motivation" of enterprise innovation through market mechanisms. First, in Hubei, all the administrative authorities should gradually reduce direct subsidies for innovation in manufacturing enterprises and establish and improve indirect subsidy mechanisms. For example, governments et al. l levels could explore and standardize the tax rebate policy for the innovation and development of different manufacturing industries and improve the efficiency of government innovation subsidies. Expanding and improving the implementation of the innovation voucher system in the entire manufacturing industry would not only lower the threshold of its utilization but also strictly control the proportion of innovation vouchers in the total investment of enterprise innovation. This would effectively expand the scope of innovation vouchers and encourage enterprises to be self-motivated in engaging in innovation while improving the precision of government technology services. Furthermore, the policies related to the innovation and development of enterprises should be streamlined and standardized. This also applies to the various systems of taxation. For instance, the financing costs of using financial technology in manufacturing enterprises or time consumption can be reduced. The costs can also be reduced by regulating the various charging behaviors and standards in the process of corporate intellectual property financing.

(3) Hubei's manufacturing industries should plan and integrate innovative resources from the national, or even global, perspective to improve their synergic innovation capability. Accelerating the innovation

and development of Hubei's manufacturing industries requires the synergic innovation of multiple entities, such as corporations, research institutes, universities, governments, and service organizations. The manufacturing industries in Hubei must not only narrow their vision to the provincial level but also focus on integrating innovation resources from the national or global arena, constructing innovative value chains, conducting in-depth innovation cooperation, and accelerating industrial innovation and development [37]. Practically, the manufacturing industries in Hubei should implement the "going global" and "bringing in" strategies simultaneously. Depending on the industry's development needs and requirements of talent resource concentration, manufacturing industries may also locate their R&D organizations in the four major Chinese cities (Beijing, Shanghai, Guangzhou, and Shenzhen) or overseas to attract talent. This will increase technological achievements in the manufacturing industries in Hubei, thereby enhancing manufacturing productivity. Concerning the key technological issues of the industry's development, the industries may consider establishing a government-led industrial synergy-innovation base that focuses on solving common innovation and development problems faced by various industries, breaking through the information "isolation" and strengthening knowledge sharing to promote the position of Hubei's manufacturing industries in the industrial value chains. This will effectively consolidate and enhance their market competitiveness.

Data Availability

The data presented in this study are available on request from the corresponding author. The data are not publicly available due to partial contents of an ongoing research project.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

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