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Evaluation and Dynamics Mechanism of the Smart Specialization Level in China's Regional Manufacturing Industry

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Abstract

Smart specialization, as an important concept in regional policy, has presented greater vitality in both theory and practice. To assess smart specialization at three different levels—smart level, specialization level, and coupling level—this paper develops an index system. We statically evaluate the level of smart specialization in the manufacturing industry in the 30 provinces and municipalities on China's mainland using the entropy weight-TOPSIS method and then use a system dynamics model to examine the dynamic development characteristics of the level of smart specialization in each region. The findings indicate that there are considerable regional differences in the development level and speed of smart specialization among provinces and municipalities. The development of the smart specialization level of manufacturing follows a "logarithmic index" curve in terms of its shape. The level of industrial smart specialization is positively impacted by the level of industrial smartness, specialization and coupling; however, this effect is critical in scale and nature. To achieve the best effects from the development of manufacturing smart specialization, a continuous, dynamic, and integrated intervention mix should be established.

Keywords

manufacturing industry; smart specialization; level evaluation; entropy power TOPSIS; system dynamics model

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1. Introduction

Over the past 40 years of reform and opening up, China has demonstrated to the world the miracle growth of its economy. With a surge in science and technology innovation capacity, China's manufacturing industry has exhibited strong potential in both scale and development momentum. To cope with a new round of scientific and industrial competition, developed countries have launched strategies of manufacturing revitalization, arming their manufacturing industry with new technology and new knowledge. Then, seizing the opportunity of innovation-driven growth momentum to realize the high-quality development of the manufacturing industry has become a real problem facing China today. The only strategic option is to follow the development path of China's specialized manufacturing industry. To promote China's manufacturing industry into the middle and high-end value chain to provide the impetus for the smart specialization development of China's manufacturing industry, we must comprehensively promote breakthrough development in key areas such as new generation information technology and intelligent manufacturing technology.

Innovation and R&D investment are deemed to be the most fundamental sources of high-quality development. In 2019, China's total investment in R&D was 2.2 trillion RMB, ranking second in the world. However, there was still a huge gap between the level of basic investment and the level of 15% to 25% in developed countries. It is evident that China's manufacturing industry still needs to be strengthened in terms of scientific and technological innovation dynamics, technological deepening and upgrading, and core competitiveness. Furthermore, China's regional resource endowments vary greatly, and there is an obvious gradient in the development level of manufacturing industries among the eastern, central, and western regions. Realizing the "localized" development of regional manufacturing industries according to different regional resource endowments to enhance the overall competitiveness of China's manufacturing industry has become an urgent problem.

To analyze the productivity gap between Europe and the United States, the EU "Knowledge Growth Group" indicates a smart specialization strategy to reflect on the logic of policy priorities that may contribute to growth based on an examination of the productivity challenges facing the region. The essence of smart specialization is how to specialize "smartly". "Smartness" is the source of the advantages of specialization, while specialization is the basis for smart development. Smart specialization helps regional economies diversify more "smartly" with the help of general-purpose technologies, thus achieving greater competitiveness of existing industries. This is due to its focus on the specific strengths of a country or region and it enhances regional diversification based on local differences. Therefore, the development of smart specialization is not only related to the difference and correlation between regions but also includes the selection of priority areas based on local differences, which presents the characteristics of complex and dynamic correlation.

Although the practice of smart specialization strategies in the EU manufacturing industry has gradually deepened, the complexity and dynamics of the development process of smart specialization in the manufacturing industry pose obstacles for academic research. Specifically, the smart specialization level is difficult to directly observe by general empirical research methods, preventing researchers from dissecting the internal operation mechanism and the dynamic relationship between smart and specializations. However, the understanding of the dynamic relationship and the operation mechanism between the two has important guiding significance for industrial innovation practice. Therefore, this study intends to unveil the operational black box of the smart specialization level of China's manufacturing industry and provides theoretical guidance for the development of the industry based on the research findings.

2. Literature Review

The core concept that needs to be clarified is the meaning of "being smart". Domestic research on the smart development of the manufacturing industry is nonexistent. The concept of smartness is proposed and deepened from the practice of smart specialization in the EU countries. Foray *et al*. (2009) argued that "being smart" is a series of processes such as identifying the region's own strengths and comparative assets. According to Attila *et al*. (2020), industrial specialization in an area is "smart" if it is derived from local traditions rather than directly imitating the success of other places. To ensure the professional diversity of relevant technologies in an area or industry, Bjorn *et al*. (2015) defined "being smart" as the process of "entrepreneur discovery". The Centre for Science, Technology and Innovation Policy Research at the University of Cambridge continued by stating that for specialization to be considered "smart", it must identify and concisely state what makes a region or industry unique in a way that is recognized by both local and outside actors. In short, "smartness" comprises not only the distinctive capabilities and assets of the region or industry but also the way in which multiple players participate in the discovery of global networks.

"Specialization" is the key problem with smart specialization in the manufacturing industry. There is a substantial corpus of empirical literature on "specialization" and its effects on local economies. Neoclassical trade theory claims that any location can benefit economically from the specialization of production in accordance with its own advantages and market advantages. Meng and Lu (2012) revealed a significant imbalance among the provinces, with Shanxi having the highest degree of division of labor in the manufacturing sector, even though all the central region's manufacturing industries were continuously improving their levels of specialization and division of labor. Shi (2021) asserted that the three provinces and one city in the Yangtze River Delta still have a low level of specialization and that no mutually advantageous industries have developed among the provinces and municipalities.

Research on the development of manufacturing smart specialization originates from the practice of the EU countries, while domestic research on manufacturing smart specialization is still in its infancy. Most studies in this regard fall into two categories. One is to offer a straightforward evaluative description. For instance, Jakopin (2017) concentrated on the state of competitiveness in the various subsectors of the manufacturing industry, as well as the benefits of foreign direct investment, ripple effects, and export competitiveness. Haukioja *et al*. (2018) evaluated the degree of smart specialization and regional industry diversification benefits using three industrial diversification dimensions, the relative gap in industrial structure, and manufacturing labor intensity. Indicators such as the employment growth rate, sales, labor productivity, export intensity, industry R&D expenditures, sales, and the number of newly registered enterprises were all examined by Kotnik and Petrin (2017) to determine the degree of industrial specialization. According to Geipele *et al*. (2015), the major assessment content for manufacturing performance evaluation includes industry competitive share, risk, growth rate, and technological intensity. This content can show the impact of commercializing smart specialization strategies on technology industries.

The other category includes the impact of smart specialization on the manufacturing sector. Specialization in high-tech manufacturing, according to Kijek *et al*. (2020), has a direct impact on regional total factor productivity. Smirnova *et al*. (2020) evaluated how new technology developments in the manufacturing sector affected regional industry specialization and demonstrated how the digital transformation of the industry had a favorable impact on changes in the economy's structure. New technologies, such as information and communication technology, are among them and have a growing impact on how local production is changing. However, Šipilova (2015) argued that improvements to economic performance are not brought about by changes in the technological structure of the manufacturing sector. Riva and zena (2018) further argued that regions with a low manufacturing development index are not suitable for high-technology manufacturing specialization strategies. Barzotto *et al*. (2020) argued that the revitalizing effect of smart specialization strategies in lagging regions has been weak and has provided only a small opportunity for the accelerated transformation of manufacturing.

However, the current domestic study on the development of smart specialization in manufacturing mostly addresses the problem of "specialization", and the research on "being smart" is barely adequate. The evaluation of manufacturing smart specialization and its impact on regional growth capacity has received increased attention in foreign studies, but no organized research has been established. Studies on the development of smart specialization in manufacturing are constrained by their approach, which is primarily concerned with providing quantitative descriptions of content and attributes. The distinctive development potential of the local industrial sector cannot be scaled by indicators or models. In conclusion, there are few studies on the effects of the coupling relationship between industrial smart development and specialization development on the overall level of smart specialization. On the one hand, the existing studies primarily evaluate the level of manufacturing smart specialization using static evaluation indicators and ignore the examination of a dynamic relationship between industrial smartness and specialization. Based on the framework of smart specialization, this paper examines the dynamic evolution of the smart level, specialization level, and coupling level in the Chinese manufacturing industry. To address the limitations of previous studies, it uses computer simulation modeling (a system dynamics approach) to thoroughly examine the relationship between the three.

3. Index for Smart Specialization Level of the Regional Manufacturing Industry

This paper begins by using Figure 1 as an illustration to help readers comprehend the idea of smart specialization in manufacturing and how it relates to other related concepts. The distinctive advantages of industries are represented by the gray rectangles in Figure 1. The terms "industrial agglomeration" and "regional specialization degree" have different meanings and do not entirely overlap, but they may. For instance, certain industries will be highly concentrated in some regions while also exhibiting the phenomenon of highly specialized industrial development. The relatedness of the domain and technology, or the idea corresponding to the rightmost oval in Figure 1, is another crucial factor considered by the concept of smart specialization. The concept of smart specialization in manufacturing comes when this feature matches the existence of highly clustered specialized development of industries in the region.

To increase the scientific credibility of the index selection in this paper, we use the CiteSpace software to conduct econometric analysis of smart specialization in manufacturing literature, to systematically sort out and comprehend the current commonly used smart specialization evaluation indices and to conduct quantitative statistics of commonly used indices.

This study builds an evaluation index system with components for analyzing an industry's competitive advantage, level of specialization, concentration of industries, and relatedness of industries. The target layer of the evaluation of the manufacturing smart specialization level, which includes the three sub-criteria layers of innovation capacity, knowledge accumulation, and benefit level, is the

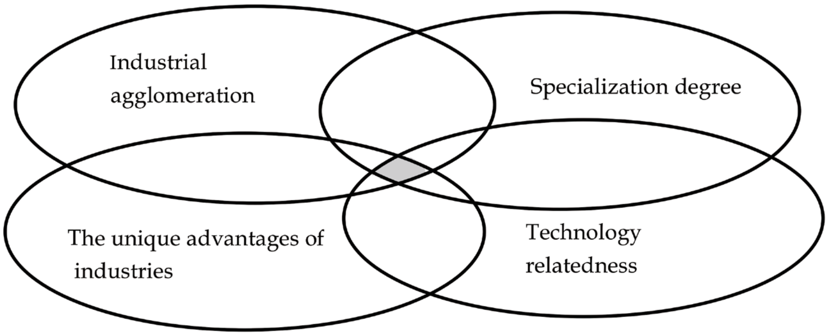

Fig. 1 Relationship between smart specialization in manufacturing and other related concepts

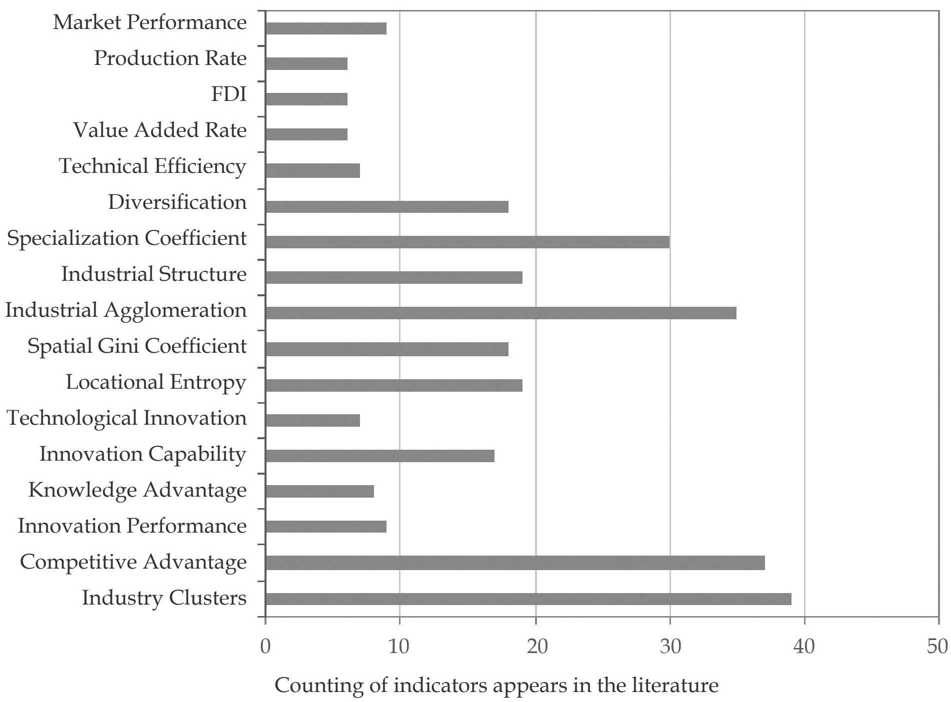

Fig. 2 Statistical chart of evaluation indicators of smart specialization in manufacturing

manufacturing smart level. The goal of innovation capacity is to illustrate the basis and potential for the regional manufacturing industry's smart development, with a focus on four indicators, including R&D investment intensity, relative R&D staff density, industry-university-research institute cooperation levels, and fixed asset investment. Knowledge accumulation, specifically the number of patents applied for by industries, the index of comparative advantage of high-tech patents, the rate of technology introduction and digestion, and the turnover of the technology market, reflects the capacity of the local manufacturing sector to absorb and digest knowledge. The benefit level indicates the standard to which regional manufacturing has advanced, considering the annual rate of increase in industrial added value, the market share of new products, and the exported volume of high-tech industrial products.

The three sub-criteria layers that make up the evaluation of the manufacturing specialization level are industry concentration, level of specialization, and industrial relatedness. Industrial concentration, which primarily includes the three sub-criteria of industrial concentration, industrial spatial aggregation degree, and industrial average concentration rate, is the external representation of manufacturing specialization. The manufacturing specialization level directly affects the degree of specialization, which primarily consists of five sub-criteria: market share, industrial sector contribution rate, total profit, and high technology industry development coefficient.

The evaluation of the manufacturing specialization level includes three sub-criteria layers: industrial concentration, degree of specialization, and industrial relevance. Industrial concentration is the external expression of manufacturing specialization, which mainly includes the three sub-criteria of industrial concentration, industrial spatial aggregation degree, and industrial average concentration rate. The degree of specialization is the direct performance of the manufacturing specialization level, which mainly includes the five sub-criteria of the industrial specialization coefficient, market share, industrial sector contribution rate, total profit, and high technology industry development coefficient. Industrial relatedness is the performance of the manufacturing sector's content, and sectors with higher levels of industrial relatedness are more likely to develop industrial specialization, which includes two indicators, which are the degree of export orientation and the average value of the similarity coefficient between industries.

Table 1 Evaluation index system of the smart specialization level of the manufacturing industry

Primary indicators	**Smart level**			**Specialization level**		
Secondary indicators	Innovation capacity (0.2912)	Knowledge accumulation (0.3888)	Benefit level (0.3005)	Industry relatedness (0.0509)	Industry concentration (0.5069)	Specialization degree (0.4422)
Tertiary indicators	R&D investment intensity (0.1085) R&D personnel density (0.1693) Degree of cooperation between industry, university and research (0.450) Fixed asset investment (0.2716)	Number of patent applications (0.3575) Comparative advantage index of high and new technology patents (0.0905) Technology introduction and digestion and absorption rate (0.2221) Technology market turnover (0.3299)	Annual growth rate of industrial value added (0.0613) Market share of new products (0.3651) Export value of high-tech industry products (0.5736)	Level of industrial outward orientation (0.1803) Mean value of industrial structure similarity coefficient (0.8197)	Industrial concentration degree (0.3332) Spatial concentration of industry (0.4205) Average industrial concentration rate (0.2463)	Industrial specialization coefficient (0.1279) Market share (0.287) Industrial sector contribution rate (0.1492) Total profit (0.2542) High-tech industry development coefficient (0.1817)

4. Evaluation Model for the Smart Specialization Level of the Regional Manufacturing Industry

4.1. Modeling purpose and main assumptions

We examine potential relationships between components and subsystems within the manufacturing smart specialization development system through model simulation. There are common principles for the development of manufacturing smart specialization, but the realistic development path is rooted in the nation's and regions' unique industrial traits. The advantages and disadvantages of various policy combinations may be examined through modeling for scenario analysis, and by utilizing the concepts of the system; hence, a clear roadmap for the development of manufacturing smart specialization in China can be created. The system dynamics model's policy experiment function can serve as a foundation for the implementation and modification of policies. The development of manufacturing smart specialization is a complicated system project that cannot be realized by a single policy or action. Additionally, the development of manufacturing smart specialization is a long-term project, and it will take a while before some policy changes bear fruit. Therefore, it is essential to thoroughly examine the impact of inputs and policy measures on the overall development level in the future when modeling the development of manufacturing smart specialization. Additionally, it is necessary to identify and address any potential issues that may arise during the development of smart specialization.

The dynamic interaction between the manufacturing smart level, specialization level, and coupling level is the first area of focus for this model. Major regulatory changes and other industry-wide influences are not considered by the modeling.

Second, the model considers the interaction between the three subsystems of the manufacturing smart level, specialization level, and their coupling levels. The growth of the manufacturing smart specialization level is a result of the three subsystems' increasing scale payoffs, which is expressed using the improved Cobb-Douglas production function.

Third, while this model assumes that chances for industrial innovation result from environmental turbulence, the industry's ability to seize those opportunities varies. While some enterprises in the sector may already be able to do so, others may not, and instead, environmental turbulence affects their degree of development. Some enterprises in the sector are able to take advantage of innovative opportunities and increase the level of industrial smart specialization. Assuming that the degree of environmental turbulence is divided into three levels: high (turbulent), medium, and low (stable), the number of innovation opportunities faced by industries will increase with the escalation in environmental turbulence when the degree of turbulence is above the medium-high level. However, the spectrum of innovation opportunities that industries may seize and employ comes from the range between medium and high levels of turbulence.

4.2. Model composition

An essential step of modeling system dynamics is creating a cause-and-effect diagram. The cause-and-effect diagram lays the groundwork for the quantitative expressions by succinctly expressing the relationships between the components of the system. Given that the manufacturing smart specialization level model comprises more variables, we must first establish the causality diagram of key variables in the model to understand the connections between the model's subsystems, as shown in Figure 3. Second, the manufacturing smart specialization model is divided into three subsystems—manufacturing smart level, manufacturing specialization level, and coupling level—to enable modeling.

4.2.1. Subsystem of smart level

The basic equation for the subsystem of the manufacturing smart level shows the increasing scale reward by time lag under the influence of the major variables which are innovation capacity, knowledge accumulation, and benefit level.

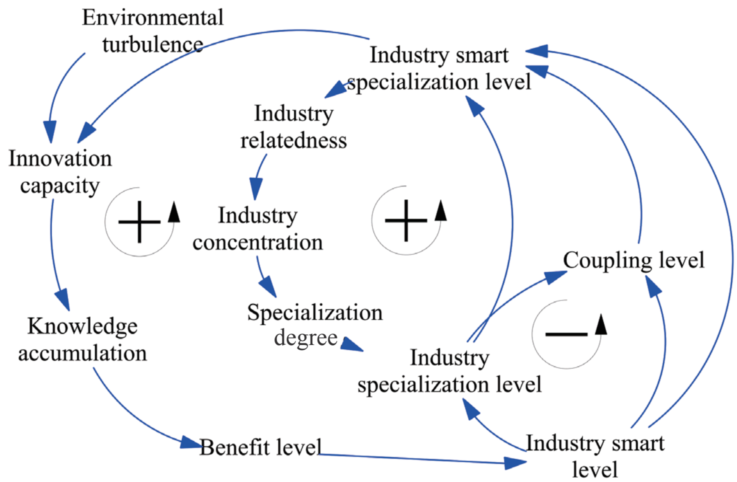

Fig. 3 Schematic diagram of the causality of the smart specialization level in the manufacturing industry

Industrial smart level = INTEGER (Smart development rate, 0)

INTEGRATION development rate = DELAY1I(Innovation capacity*0.2912+Knowledge accumulation*0.3888+Benefit level*0.3005,6, 0)*DELAY1I(EXP(-Time/3), 2, 4)

Innovation capacity = R&D investment intensity*0.1085 + R&D personnel density*0.1693 + Degree of cooperation between industry, university and research*0.4507 + Fixed asset investment*0.2716

Knowledge accumulation = Number of patent applications*0.3575+High-tech patent comparative advantage index*0.0905+Technology introduction and digestion rate*0.2221+Technology market turnover*0.3299

Benefit level = Annual growth rate of industrial value added*0.0613+ Market share of new products*0.3651+ Export value of high-tech industrial products*0.5+ Number of grasping opportunities*0.0736

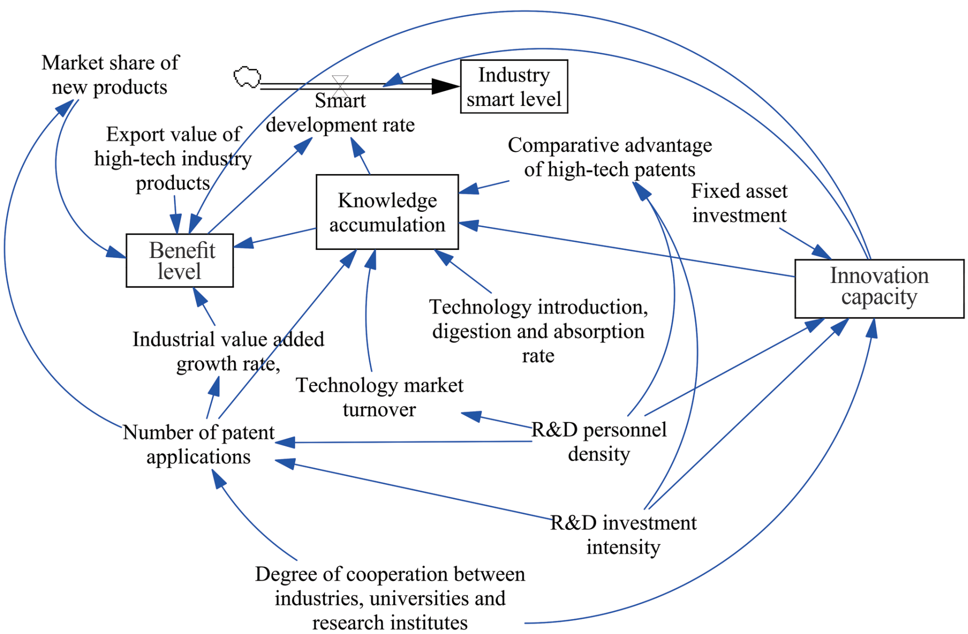

Fig. 4 Subsystem of smart level

4.2.2. Subsystem of specialization level

The basic equation for the subsystem of the manufacturing specialization level is as follows. It considers the main factors of industrial relatedness, industrial concentration, and level of specialization and shows the increasing effect of scale reward by time lag.

Industry specialization level = INTEGER (Specialization development rate, 0)

Specialization development rate = DELAY1I (Specialization degree * 0.4422 + Industry concentration * 0.5069 + Industry relatedness * 0.0509, 6, 0) *DELAY1I (EXP (-Time/3), 2, 4)

Industry Concentration = Industrial concentration rate*0.332+Dagree of industrial spatial agglomeration*0.4205+Average industrial concentration rate*0.2463

Specialization degree = Industry specialization coefficient*0.1279+Market share*0.287+Industry sector contribution rate*0.1492+total profit*0.2542+High-tech industry development coefficient+0.1817

Industry relatedness = Level of industrial outward orientation*0.1803+ Similarity coefficient of industrial structure *0.8197

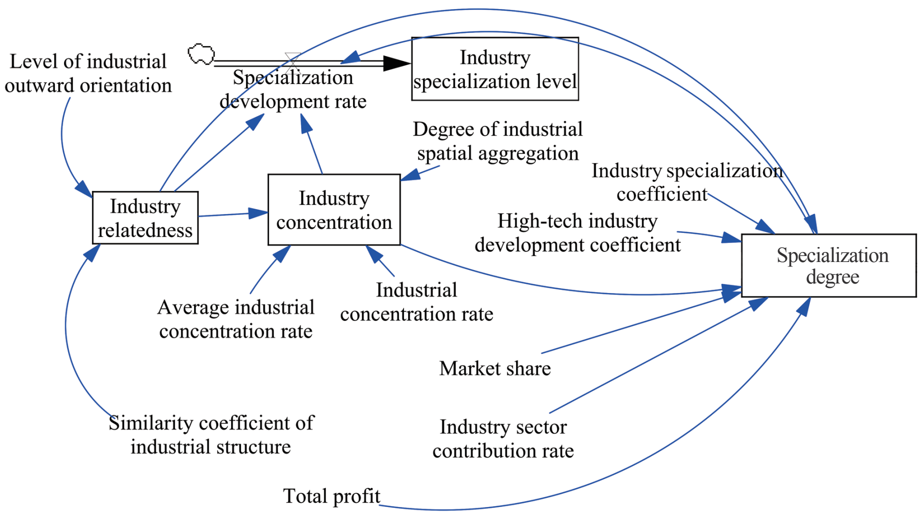

Fig. 5 Subsystem of specialization level

4.2.3. Subsystem of coupling level

The degree of coupling between the industrial smart level and the specialization level also exhibits a lag in continuous growth over time. At the same time, different manufacturing smart levels and specialization levels exhibit coupling levels with significant differences, and the development of the Chinese manufacturing smart level subsystem and the specialization level subsystem is influenced by exogenous parameters and exhibits some periodicity. To determine the coupling coordination degree of many subsystems, this paper uses the physics concepts of capacity coupling and the coupling coefficient model. The main equation is given below.

$$\text{Coupling degree} = \sqrt{\frac{\text{Industry smart level} * \text{Industry specialization level}}{\text{Industry smart level} + \text{Industry specialization level}}}$$

Comprehensive coordination index = 0.5*Level of industry smartness + 0.5*Level of industry specialization

Coupling coordination level = $\sqrt{\text{Coupling level} * \text{Comprehensive coordination index}}$

Coupling level development rate = Coupling coordination degree * DELAY1I(EXP(-Time/3), 2, 4)

Coupling level = INTEGER (Coupling level development rate, 0)

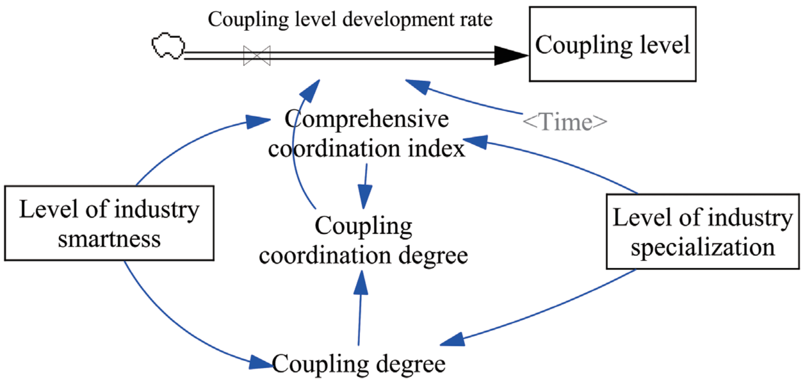

Fig. 6 Subsystem of coupling level

4.2.4. System of smart specialization level

Three subsystems—industry smart level, specialization level, and coupling level—that influence and interact with one another are shown in the manufacturing smart specialization level system. The development of the manufacturing smart specialization level is promoted through interactive feedback among subsystems. The key to the evaluation of the manufacturing smart specialization level lies in the effective measurement of the rate of smart specialization improvement and the rate of smart specialization decline. The scale effect spillover in the life cycle of manufacturing smart specialization reflects the mutual feedback between the three subsystems, and the main equation is as follows.

Industry smart specialization level = INTEGER (Smart specialization increase rate - Smart specialization decrease rate, 0)

Smart specialization increase rate = DELAY1I (Industry specialization level * 0.3 + Industry smart level * 0.3 + Coupling degree * 0.4, 4, 0) *DELAY1I(EXP(-Time/3), 3, 4)

Smart specialization decrease rate = IF THEN ELSE (ABS (Environmental turbulence) >= 0.75, Industry smart specialization level*0.03, Industry smart specialization level*0.01)

Environmental turbulence=RANDOM UNIFORM (-1, 1, 0.5)

Innovation opportunity=IF THEN ELSE (Environmental turbulence>=0.5, Environmental turbulence, 0)

Accumulation rate = DELAY1I (Innovation opportunity, 6, 0) *DELAY1I (EXP (-Time/3), 2, 4)

Market opportunities = INTEGER (Accumulation rate, 0)

Number of opportunities to grasp = Industry smart specialization level * Market opportunities

4.3. Parameters and scenario settings

The parameters in the system dynamics model include constant values, auxiliary variable values, and functions. The model's parameters that do not change considerably over time are treated as constant values to make it simpler. Some of the variables, such as the level of manufacturing smart and specialization, have initial values set to 0 because realistic information is not yet accessible for them. By comparing the simulation results with the static evaluation result data, various parameters are adjusted during the model calibration process to maximize the output of the model. There are two ways to set auxiliary variables and constants. A few data sources, including the China Statistical Yearbook and various industrial statistical yearbooks, are one. The second is the quantitative expressions in both local and international researchers' studies. Eleven level variables, 6 rate variables, 6 auxiliary variables, and 16 constants make up the system of the smart specialization level, as indicated in Table 2.

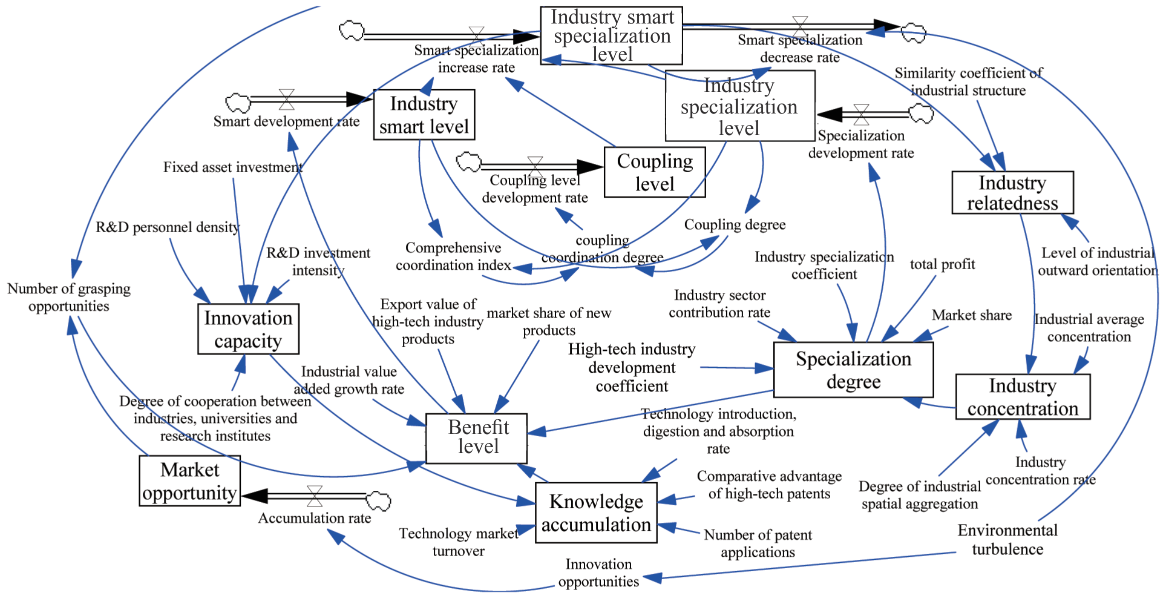

Fig. 7 System of smart specialization level

The "industry smart specialization level," "industrial specialization level," "industrial smart level," and "coupling level" are the four main variables of the system. Three components make up the industrial smart level: benefit level, knowledge accumulation, and innovation capacity. Industrial relatedness, industrial concentration, and specialization level are the three components that make up the level of industrial specialization. The three dimensions of coupling degree, coupling coordination degree, and comprehensive coordination index make up the level of coupling. The auxiliary variables include the coupling degree, coupling coordination degree, comprehensive coordination index, number of grasping opportunities, innovation opportunities, and environmental turbulence. Environmental turbulence is an exogenous variable with random characteristics, so it is set as a random variable, taking the values [-1,1], and assuming that when environmental turbulence is at [-0.5,0.5], the environment is at a stable level (low level), and when the absolute value is greater than 0.5, environmental turbulence threatens the development of industrial smart specialization. On the one hand, it accelerates knowledge depreciation and causes the development rate of smart specialization to decrease. On the other hand, it breeds new innovation opportunities and is a new development opportunity for the industry.

The model's parameters can all be changed, and doing so will alter the outcomes and create a new simulation of the scenario. This paper adjusts and simulates six parameters that affect the level of industrial smartness and specialization, including innovation capacity, knowledge accumulation, benefit level, industrial relatedness, industrial concentration, and specialization, to facilitate a clear understanding of the development path of smart specialization in China's manufacturing industry, and to observe the impact and potential changes of these parameter adjustments on the future development of manufacturing. The six parameters were altered with matching additions, deletions, and different combinations, establishing three classes of benchmark scenario, single scenario, and multiple scenario comparison analysis. A benchmark scenario was built up in accordance with the current data parameters. All scenarios were set for 50 years, and the parameters were simulated according to the specified years for the goal of evaluating potential future situations, drawing on currently available pertinent research and common sense.

Table 2 Variable classification of the evaluation system of the smart specialization level in the manufacturing industry

Variable Type	Parameter
Level Variables	Industry smart specialization level, industry specialization level, industry smart level, coupling level, innovation capacity, benefit level, knowledge accumulation, specialization degree, industry concentration, industry relatedness, market opportunity
Rate variable	Smart specialization increase rate, Smart specialization decrease rate, Smart development rate, Specialization development rate, Coupling level development rate, Accumulation rate
Auxiliary Variables	Coupling degree, coupling coordination degree, comprehensive coordination index, number of grasping opportunities, innovation opportunities, environmental turbulence
Constants	Fixed asset investment, R&D personnel density, degree of cooperation between industries, universities and research institutes, R&D investment intensity, industrial value added growth rate, export value of high-tech industry products, market share of new products, technology introduction, digestion and absorption rate, comparative advantage of high-tech patents, number of patent applications, technology market turnover, degree of industrial spatial aggregation, industrial concentration, average industrial concentration rate, similarity coefficient of industrial structure, level of industrial outward orientation

5. Dynamic Simulation of the Regional Manufacturing Smart Specialization Level

5.1. Static level evaluation

This paper carries out a static comprehensive evaluation of the level of smart specialization (S3) of 30 provinces and municipalities of China's mainland from 2010-2018 based on the results of the coupling degree evaluation and the entropy-weighted TOPSIS method. Figure 8 and Table 3 show that from 2010 to 2018, China's manufacturing smart specialization's coordination degree assessment value fluctuated and fell from 0.235 to 0.2249. Additionally, although there has not been much growth, China's average value for manufacturing smart specialization is generally consistent. Between 2010 and 2013, the level of manufacturing smart specialization among them decreased to 0.1563; then, between 2014 and 2018, it started to climb flatly in 30 regions of China's mainland until stabilizing at 0.1622.

This is perhaps because both the smart level subsystem and the specialization level subsystem have an impact on the development level of manufacturing smart specialization. The level of specialization in China's manufacturing sector fell precipitously between 2012 and 2013, and the rate of development slowed down in the subsequent year. This had an impact on the rate and degree of development of the manufacturing sector's comprehensive level of smart specialization. China's manufacturing industry specialization level may be significantly impacted by the implementation of manufacturing transformation and upgrading initiatives, the restriction of outdated and energy-intensive industries, the ongoing adjustment of the manufacturing industry's development structure, and the impact of the manufacturing market's performance, all of which have an impact on the manufacturing industry's smart specialization level in the region.

In terms of the coupling and coordination degree of smart specialization, the eastern region has a high coupling and coordination degree, the central region provinces have a higher coupling and coordination degree and are improving more quickly, and the northeast and western regions have a lower coupling

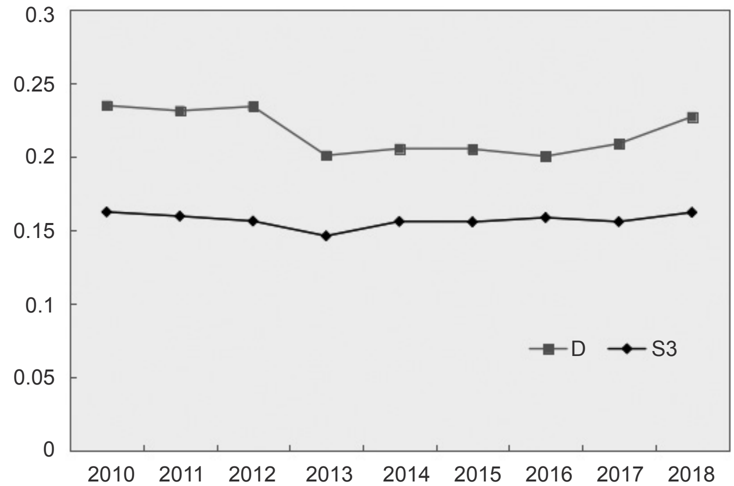

Fig. 8 The levels of smart specialization and coupling coordination in China's manufacturing industry

and coordination degree. The eastern region's provinces and municipalities are robust, the central region's manufacturing smart specialization level is improving more quickly, and the western and northeastern areas' manufacturing smart specialization levels are weaker. The level of manufacturing smart specialization in various provinces and municipalities reveals clear regional disparities based on the thorough evaluation value. The eastern region has evident advantages in the development of manufacturing smart specialization, the center and northeastern regions have distinct advantages in the development of smart specialization, and the western provinces have relatively low levels of smart specialization development.

5.2. Benchmark scenario analysis

Figure 9 illustrates how, in general, the manufacturing smart levels follow a curve that resembles a "logarithmic function". Improvements in knowledge accumulation, innovation capability, and benefit level all increase the level of industrial smartness, but there is a "critical scale" effect. The industry activates knowledge and creates new knowledge through the improvement of innovation capacity, internal and external knowledge sharing, and accumulation to improve the output efficiency of the industry. This is based on the continuous improvement of innovation capacity, knowledge accumulation, and benefit level. The level of industrial smartness initially increases quickly, but as industry develops, the level of smart specialization gradually declines until it reaches a specific level. Although after the maturity of industrial development, knowledge accumulation and structure have been developed, and the increment of new knowledge innovation is generally small, developing sectors may have more prospects for innovation. The higher development rate in the early stage and the slower development rate in the later stage, which stabilized at a given level, are mirrored in the manufacturing smart development process.

According to Figure 10, the manufacturing specialization level's development process resembles the smart development level's, which has a "logarithmic function"-shaped curve. Although it has the impact of a "critical scale," the level of industrial specialization increases as industrial relatedness, industrial concentration, and specialization degree grow. Innovation subjects with a close knowledge space within the industry are more likely to obtain spillover effects through imitation innovation and knowledge sharing, attracting further industrial concentration in knowledge space and geography, thereby enhancing the level of industrial specialization.

Table 3 Ranking of manufacturing specialization level and coupling coordination degree of provinces and municipalities in 2010, 2014 and 2018

Province/City	2010			2014			2018		
	Smart specialization level	D-value	Ranking	Smart specialization level	D-value	Ranking	Smart specialization level	D-value	Ranking
Beijing	0.4769 (3)	0.4216 (3)	3	0.4985 (2)	0.3646 (3)	2	0.4879 (2)	0.329 (5)	3
Tianjin	0.1299 (12)	0.2183 (12)	12	0.1354 (14)	0.2032 (10)	12	0.1253 (16)	0.1724 (18)	18
Hebei	0.1311 (11)	0.2247 (11)	11	0.1013 (19)	0.1756 (16)	19	0.0958 (19)	0.1755 (17)	20
Shanxi	0.1016 (18)	0.1643 (20)	19	0.051 (27)	0.1041 (27)	27	0.047 (27)	0.1095 (26)	26
Inner Mongolia	0.0776 (25)	0.1407 (26)	25	0.0439 (28)	0.0931 (28)	28	0.0458 (28)	0.1072 (27)	28
Liaoning	0.1371 (10)	0.2397 (9)	10	0.1123 (17)	0.1845 (14)	15	0.1167 (17)	0.1904 (15)	16
Jilin	0.0958 (20)	0.167 (17)	18	0.0754 (24)	0.1364 (23)	24	0.0617 (24)	0.1192 (25)	24
Heilongjiang	0.0885 (21)	0.1664 (18)	20	0.124 (15)	0.1692 (19)	18	0.1508 (12)	0.1649 (19)	14
Shanghai	0.381 (4)	0.412 (4)	4	0.248 (4)	0.2751 (6)	5	0.2472 (6)	0.2877 (7)	6
Jiangsu	0.5114 (2)	0.5912 (2)	2	0.4127 (3)	0.4826 (2)	2	0.4385 (3)	0.5629 (2)	2
Zhejiang	0.2739 (5)	0.4046 (6)	5	0.2123 (7)	0.2961 (5)	6	0.2642 (5)	0.4136 (4)	5
Anhui	0.1063 (16)	0.1853 (16)	15	0.1178 (16)	0.1826 (15)	15	0.1374 (14)	0.2237 (11)	11
Fujian	0.1474 (7)	0.2525 (7)	7	0.1107 (18)	0.1886 (13)	15	0.1375 (13)	0.2658 (9)	10
Jiangxi	0.0853 (23)	0.1647 (19)	22	0.0896 (22)	0.1578 (20)	21	0.0934 (20)	0.1913 (14)	19
Shandong	0.261 (6)	0.4055 (5)	5	0.248 (4)	0.3416 (4)	4	0.2777 (4)	0.4495 (3)	4
Henan	0.1394 (9)	0.2511 (8)	8	0.1567 (10)	0.243 (7)	7	0.174 (8)	0.3089 (6)	7
Hubei	0.1148 (15)	0.2083 (13)	14	0.14 (13)	0.2086 (9)	10	0.1631 (9)	0.2509 (10)	9
Hunan	0.1006 (19)	0.1897 (15)	16	0.144 (12)	0.1993 (12)	12	0.1261 (15)	0.2087 (12)	13
Guangdong	0.5869 (1)	0.6551 (1)	1	0.5018 (1)	0.5975 (1)	1	0.5221 (1)	0.6454 (1)	1
Guangxi	0.0809 (24)	0.1511 (23)	24	0.0781 (23)	0.1399 (22)	22	0.078 (22)	0.1275 (22)	23
Hainan	0.1051 (17)	0.142 (24)	21	0.2278 (6)	0.1736 (17)	11	0.0854 (21)	0.1266 (23)	22
Chongqing	0.0713 (27)	0.1408 (25)	26	0.0981 (20)	0.1541 (21)	20	0.1037 (18)	0.1922 (13)	15
Sichuan	0.1438 (8)	0.2356 (10)	9	0.1523 (11)	0.2224 (8)	8	0.1831 (7)	0.2874 (8)	8
Guizhou	0.0733 (26)	0.1386 (27)	27	0.0647 (25)	0.1237 (25)	25	0.061 (25)	0.1214 (24)	25
Yunnan	0.0855 (22)	0.1522 (22)	23	0.0638 (26)	0.1209 (26)	26	0.0678 (23)	0.1637 (20)	21

(continued)

Table 3. (continued)

Province/City	2010			2014			2018		
	Smart specialization level	D-value	Ranking	Smart specialization level	D-value	Ranking	Smart specialization level	D-value	Ranking
Shaanxi	0.1211 (13)	0.19 (14)	13	0.1596 (9)	0.1998 (11)	9	0.1551 (10)	0.1891 (16)	12
Gansu	0.117 (14)	0.1532 (21)	17	0.095 (21)	0.1348 (24)	22	0.154 (11)	0.1442 (21)	17
Qinghai	0.0581 (28)	0.1071 (28)	28	0.0319 (29)	0.069 (29)	29	0.0396 (29)	0.0826 (30)	29
Ningxia	0.0257 (30)	0.068 (30)	30	0.0215 (30)	0.054 (30)	30	0.0325 (30)	0.0882 (29)	30
Xinjiang	0.0464 (29)	0.1058 (29)	29	0.1645 (8)	0.172 (18)	14	0.05 (26)	0.0888 (28)	27

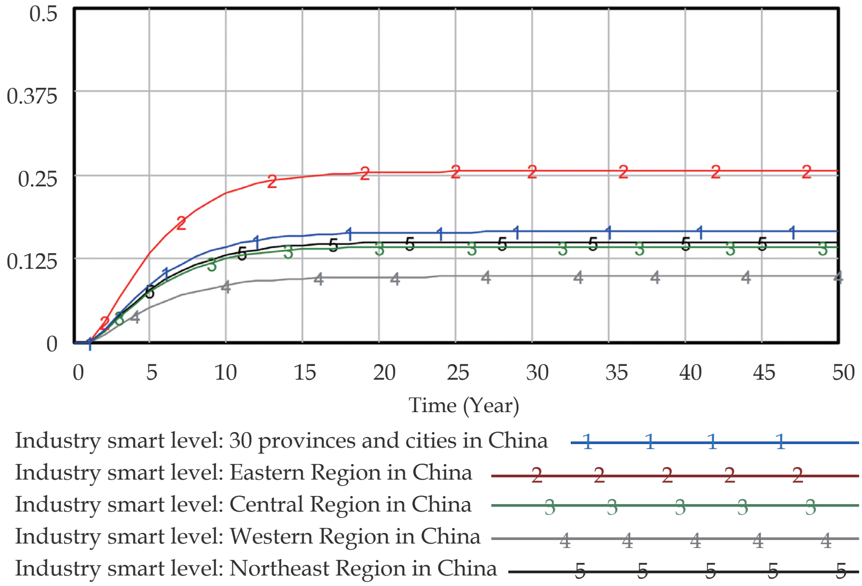

Fig. 9 Evolution of the smart level in the four major regions

Figure 11 illustrates how the level of specialization and level of smartness, which take the form of a "logarithmic function" curve, influence the level of coupling in the industry. The levels of smartness and specialization in manufacturing interact intricately. The ability to innovate better attracts industrial clustering and makes it more feasible to increase industrial concentration; this, in turn, serves to advance industrial development and increases the added value of resources as well as the output effectiveness of the innovation system. The improvement of industrial connectedness also contributes to the accumulation of knowledge innovation and can serve as a solid platform for the application of technology and patents in upstream and downstream sectors. In addition to improving the comparative advantage of industries and fully stimulating the endowment of regional resources, the identification and development of new technological applications and R&D activities can also foster the development of industrial specialization. The development state of mutual coupling and resonance between smart manufacturing and specialization is created in this manner.

The development of the level of smart specialization in manufacturing is depicted in Figure 12 in the form of a logarithmic function curve. Because environmental turbulence can be cumulative in nature, it has a dual impact on the degree of smart specialization. With the emergence of environmental turbulence, on

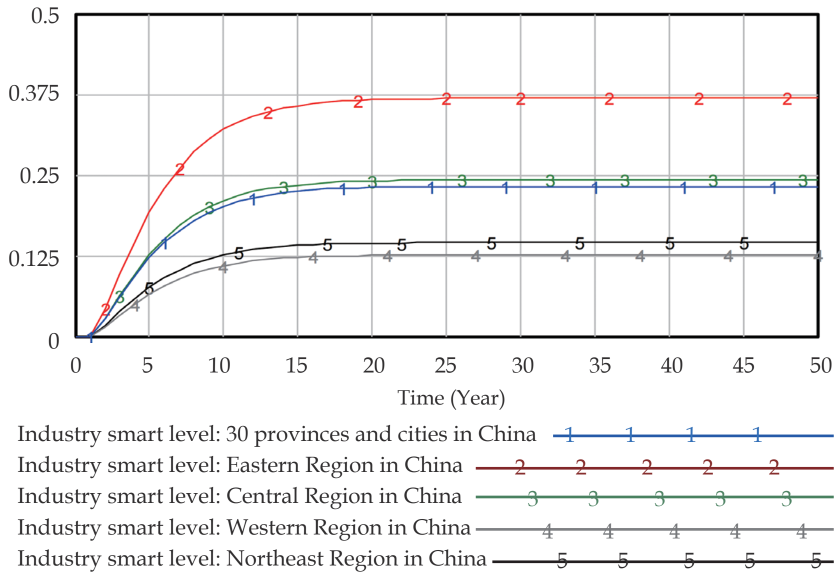

Fig. 10 Evolution of the specialization level in the four major regions

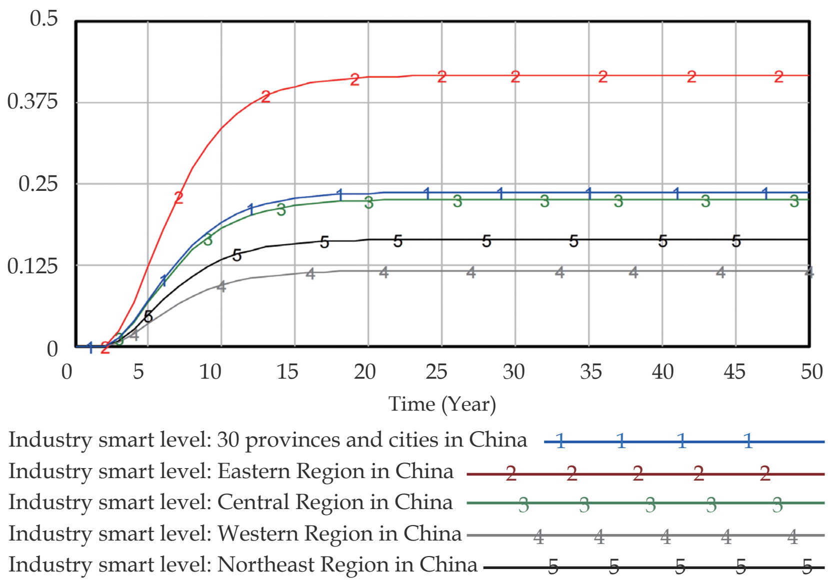

Fig. 11 Evolution of the coupling level in the four major regions

the one hand, new innovation opportunities are created; on the other hand, external pressure on industrial innovation subjects to update and create knowledge, the level of knowledge accumulation is continuously increased; the innovation spillover effect is more apparent; the correlation and concentration of interindustry knowledge increase rapidly; and the degree of specialization also makes a marginal growth contribution to growth. However, it is unlikely that all industrial innovation agents would be able to take advantage of the opportunities created by environmental turbulence, and the decline of manufacturing smart specialization is accelerated by knowledge decay and capacity decay. With slower development in the later stages and faster development in the earlier stages, the combined effect of the rising rate of manufacturing smart specialization and the declining rate of manufacturing smart specialization affects the level of manufacturing smart specialization with a lag before stabilizing at a certain level.

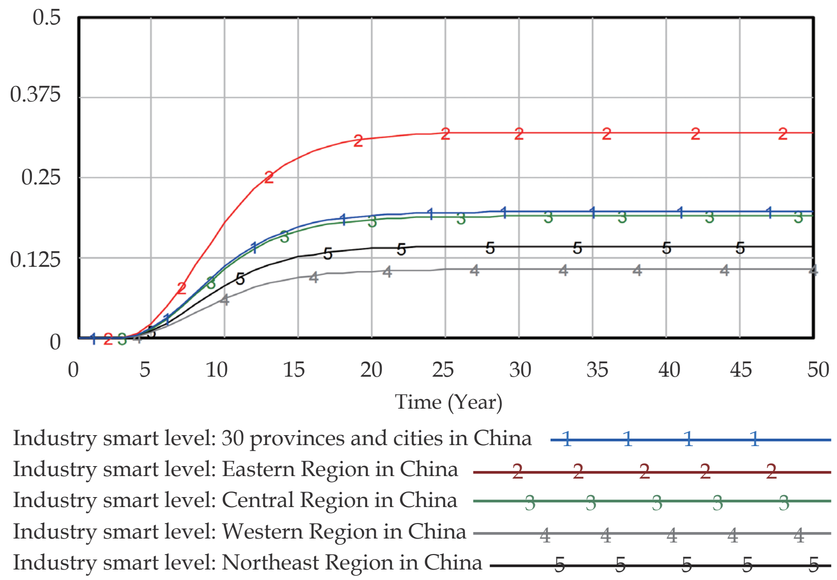

Fig. 12 Evolution of the smart specialization level in the four regions

5.3. Comparative analysis of a single scenario

Single scenario analysis focuses on the impact of the adjustment of smart level or specialization level indicators on the level of smart specialization. The scenarios for adjusting the smart level indicators are divided into three scenarios, namely, adjusting one, two, and three indicators. The same three scenarios are also included for adjusting the specialization level indicators. Since the coupling level is highly connected with the smart level and specialization level, adjusting the smart level indicators or specialization level indicators is equivalent to adjusting the coupling level; thus, the adjustment of the coupling level is not considered here.

5.3.1. Adjustment of smart level indicators

Figures 13-15 present the effects of adjusting one smart level indicator on the level of industrial smart specialization. The results show that innovation capacity, benefit level, and knowledge accumulation all have positive effects on the development of industrial smart specialization. An adjustment upward or downward of the innovation capacity from the benchmark scenario leads to an increase in the smart specialization level by 0.025 or a decrease by 0.0337 from the benchmark scenario. This proves that innovation capacity exerts a greater impact on the industry smart specialization level. An adjustment of the industrial efficiency level results in an increase of 0.0172 or a decrease of 0.0226 in the industrial smart specialization level compared to the benchmark scenario, indicating that the industrial efficiency level has a relatively smaller impact on the level of industrial smart specialization compared to the indicator of innovation capacity? When the industry benefit level is adjusted upward or downward from the benchmark scenario, the industry smart specialization level increases by 0.0233 or decreases by 0.0237 compared to the benchmark scenario. This indicates that knowledge accumulation has a smaller impact on the industry smart specialization level.

Figure 16 shows the effect of adjusting two indicators of smart level on the level of industrial smart specialization. When the two indicators of innovation capacity and knowledge accumulation simultaneously increase by 25% and 75%, the industrial smart specialization level is 0.2178 and 0.2535, respectively. The two indicators of innovation capacity and benefit level increase simultaneously by

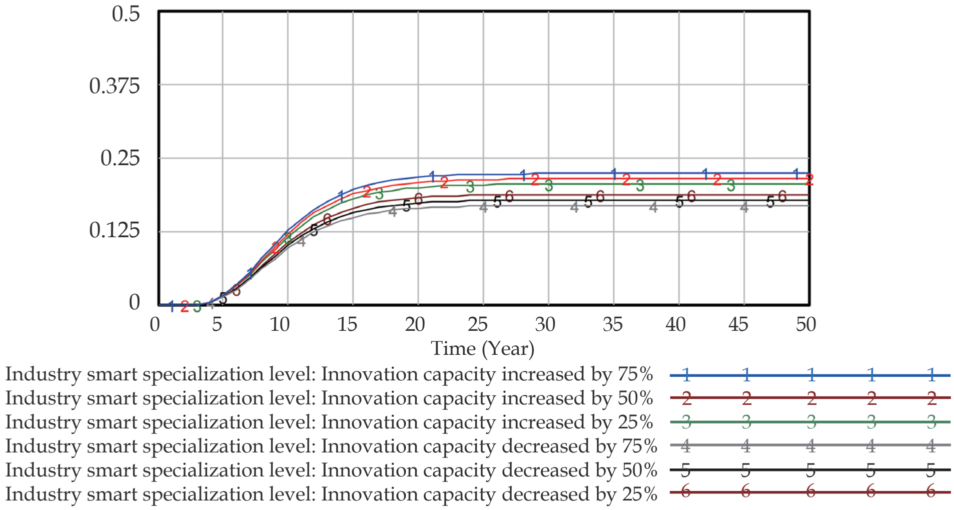

Fig. 13 The level of smart specialization after increasing and decreasing innovation capacity

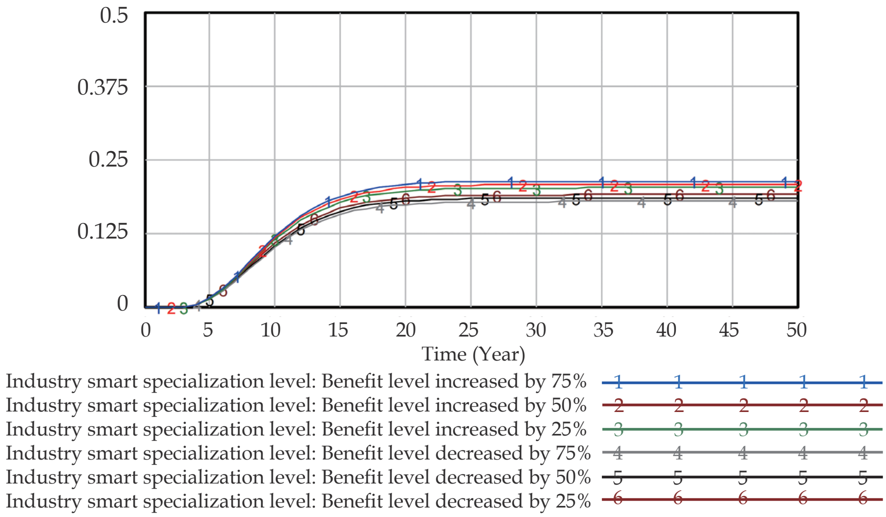

Fig. 14 The level of smart specialization after increasing or decreasing the benefit level

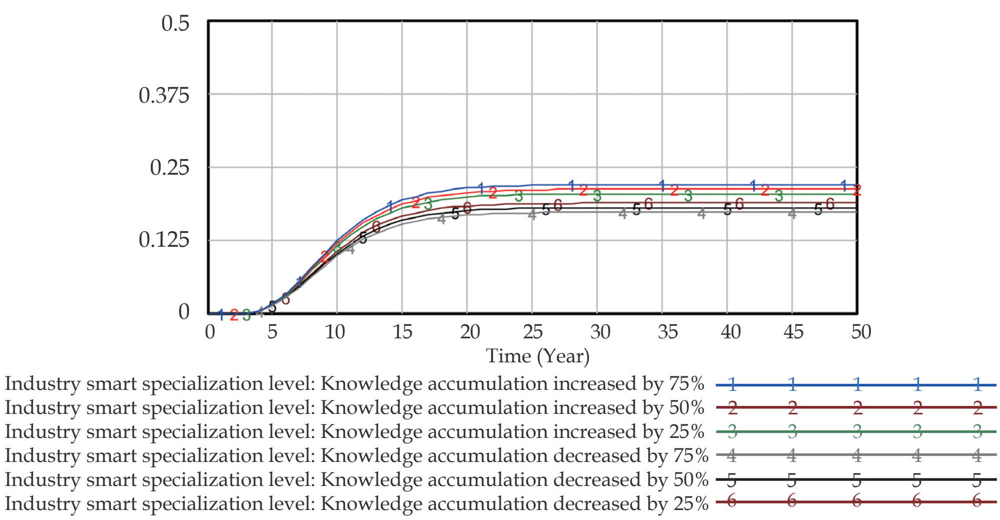

Fig. 15 The Level of smart specialization after increasing or decreasing knowledge accumulation

25% and 75%, and the industry smart specialization level is 0.2179 and 0.2302. The level of knowledge accumulation and benefit increase simultaneously by 25% and 75%, respectively, and the industrial smart specialization level is 0.2245 and 0.2438, respectively. When the two indicators of innovation capacity and knowledge accumulation decrease by 25% and 75% at the same time, the level of industrial smart specialization attains 0.1860 and 0.1509, and when the two indicators of innovation capacity and benefit level decrease by 25% and 75% at the same time, the level of industrial smart specialization attains 0.188 and 0.1575. While both indicators of knowledge accumulation and benefit level decrease by 25% and 75%, respectively, the level of industrial smart specialization is 0.1893 and 0.1613.

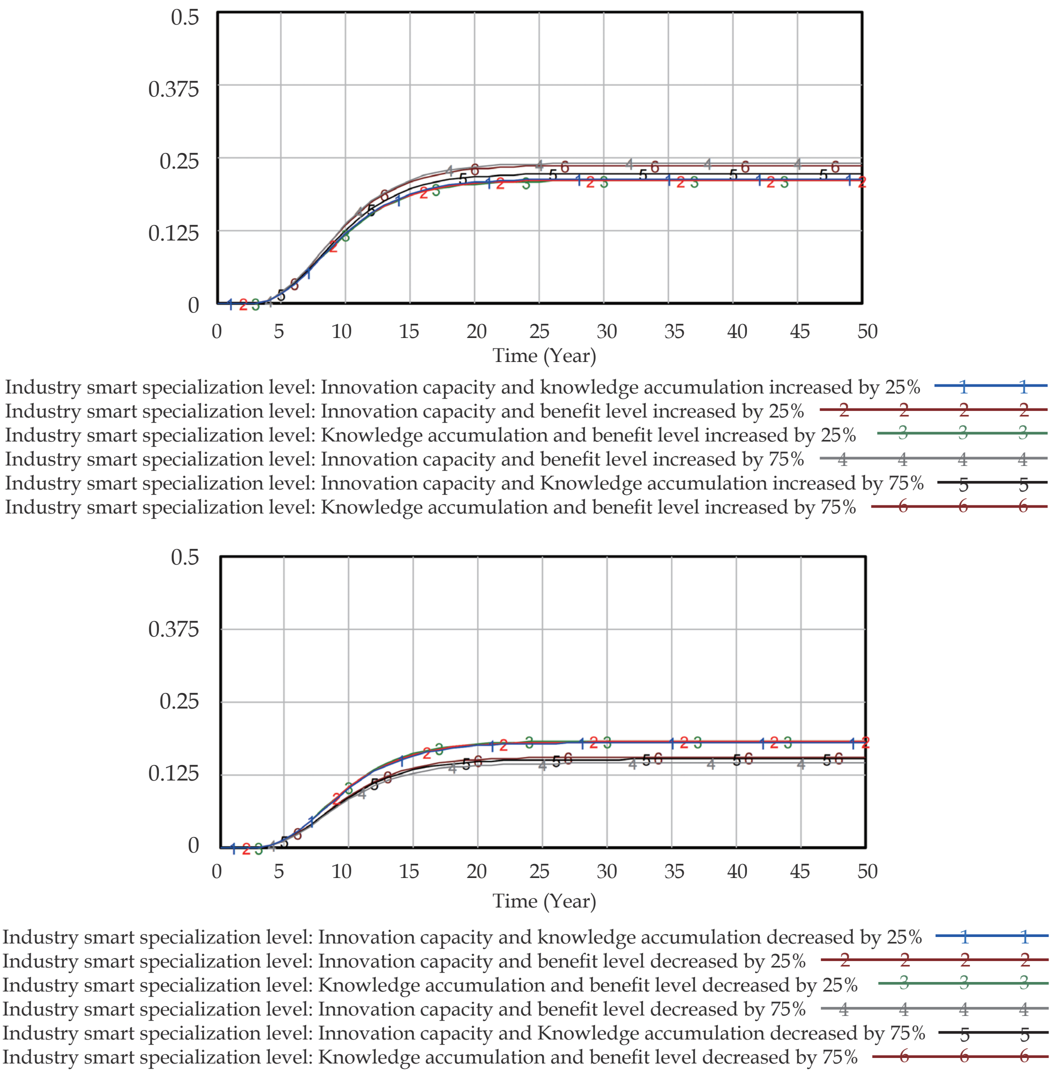

Fig. 16 The level of smart specialization after increasing or decreasing two indicators

Figure 17 illustrates the effect of adjusting three indicators of smart level on the level of industrial smart specialization. An increase of 25% and 75% of all three indicators of innovation capacity, knowledge accumulation, and benefit level results in industrial smart specialization scores of 0.2257 and 0.2706, respectively. A decrease of 25% and 75% of all three indicators simultaneously brings about industrial smart specialization scores of 0.1801 and 0.1316, respectively.

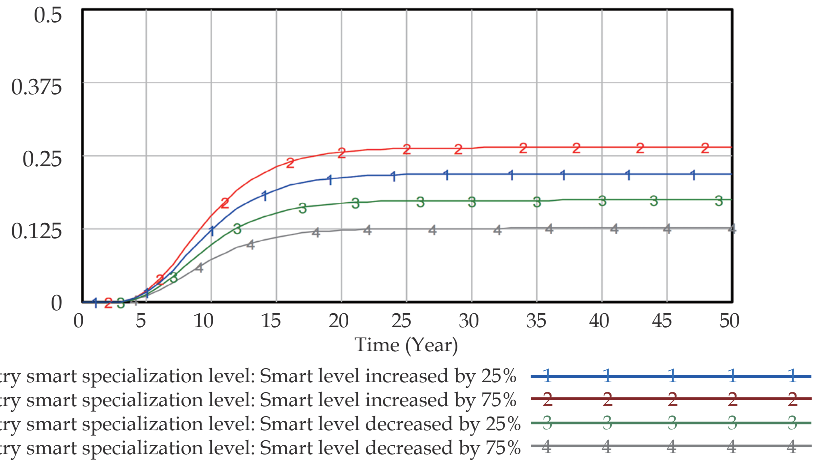

Fig. 17 The level of smart specialization after increasing or decreasing the three indicators

5.3.2. Adjustment of specialization level indicators

The impacts of changing one specialization level indicator on the level of industry smart specialization are depicted in Figures 18-20. The findings demonstrate that industry relatedness, level of specialization, and industry concentration all positively influence the growth of industry smart specialization. In comparison to the benchmark scenario, the level of industry smart specialization increases by 0.011 or decreases by 0.0111 when industry relatedness is adjusted up or down depending on the benchmark scenario. This suggests that the degree of industry smart specialization is not significantly affected by changes in industry relatedness. The level of industry smart specialization increases by 0.0458 or decreases by 0.0461 in comparison to the benchmark scenario when the level of specialization is adjusted through increasing or decreasing based on the benchmark scenario. This suggests that the amount of industry smart specialization is significantly impacted by changes in the level of specialization. The level of industry smart specialization increases by 0.0338 or declines by 0.0278 in comparison to the benchmark scenario when industry concentration is adjusted for growth or decline based on the benchmark scenario. This suggests that the level of industry smart specialization is significantly influenced by changes in industry concentration.

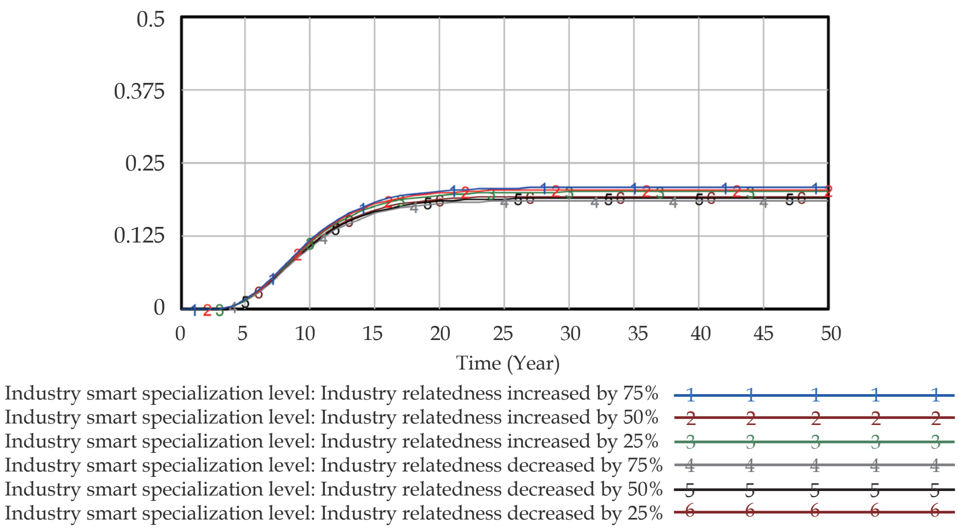

Fig. 18 The level of smart specialization after increasing and decreasing industry relatedness

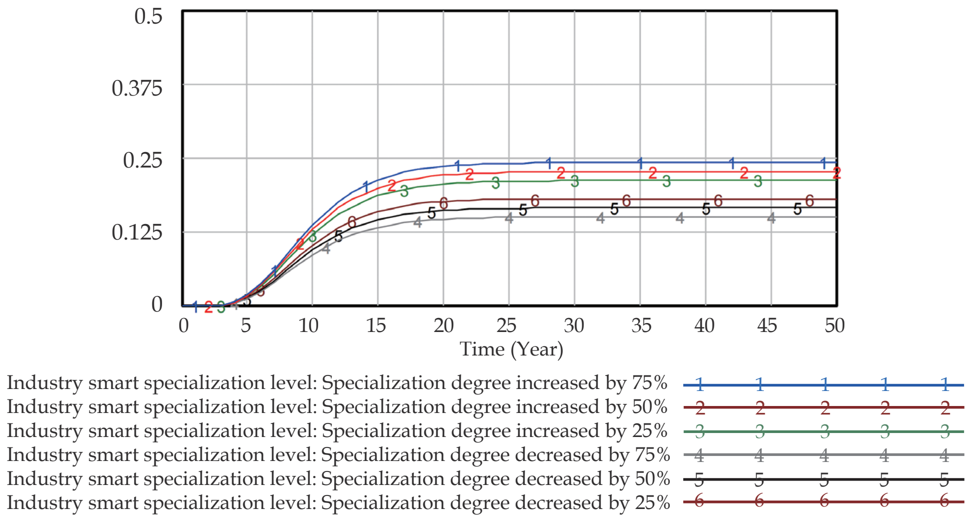

Fig. 19 The level of smart specialization after increasing and decreasing specialization degree

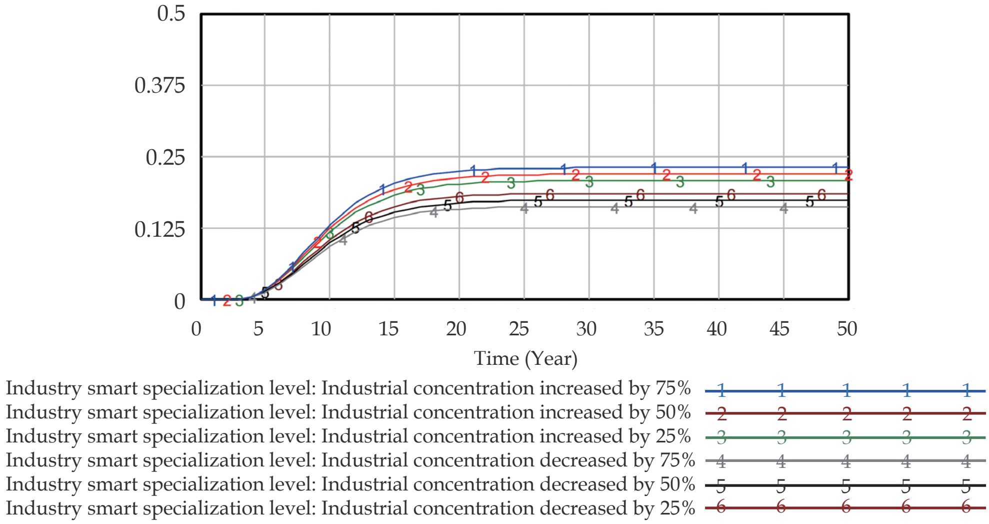

Fig. 20 The level of smart specialization after increasing and decreasing industrial concentration

The impact of adjusting two specialization level indicators on the level of industry smart specialization is demonstrated in Figure 21. The level of industrial smart specialization is 0.1807 and 0.1505, respectively, when the two indicators of industrial relatedness and industrial concentration decline by 25% and 75% at the same time. The levels of industrial smart specialization are 0.1767 and 0.1384, respectively, when the two indicators of industrial relatedness and specialization decline by 25% and 75%, respectively. When the two indicators of industrial relevance and concentration increase by 25% and 75% simultaneously, the level of industrial smart specialization attains 0.2107 and 0.2405, respectively, and when the two indicators of industrial relevance and degree of specialization increase by 25% and 75% simultaneously, the level of industrial smart specialization attains 0.21. When the two indicators of industry concentration and specialization increase by 25% and 75%, respectively, the level of industry smart specialization attains 0.2222 and 0.2751.

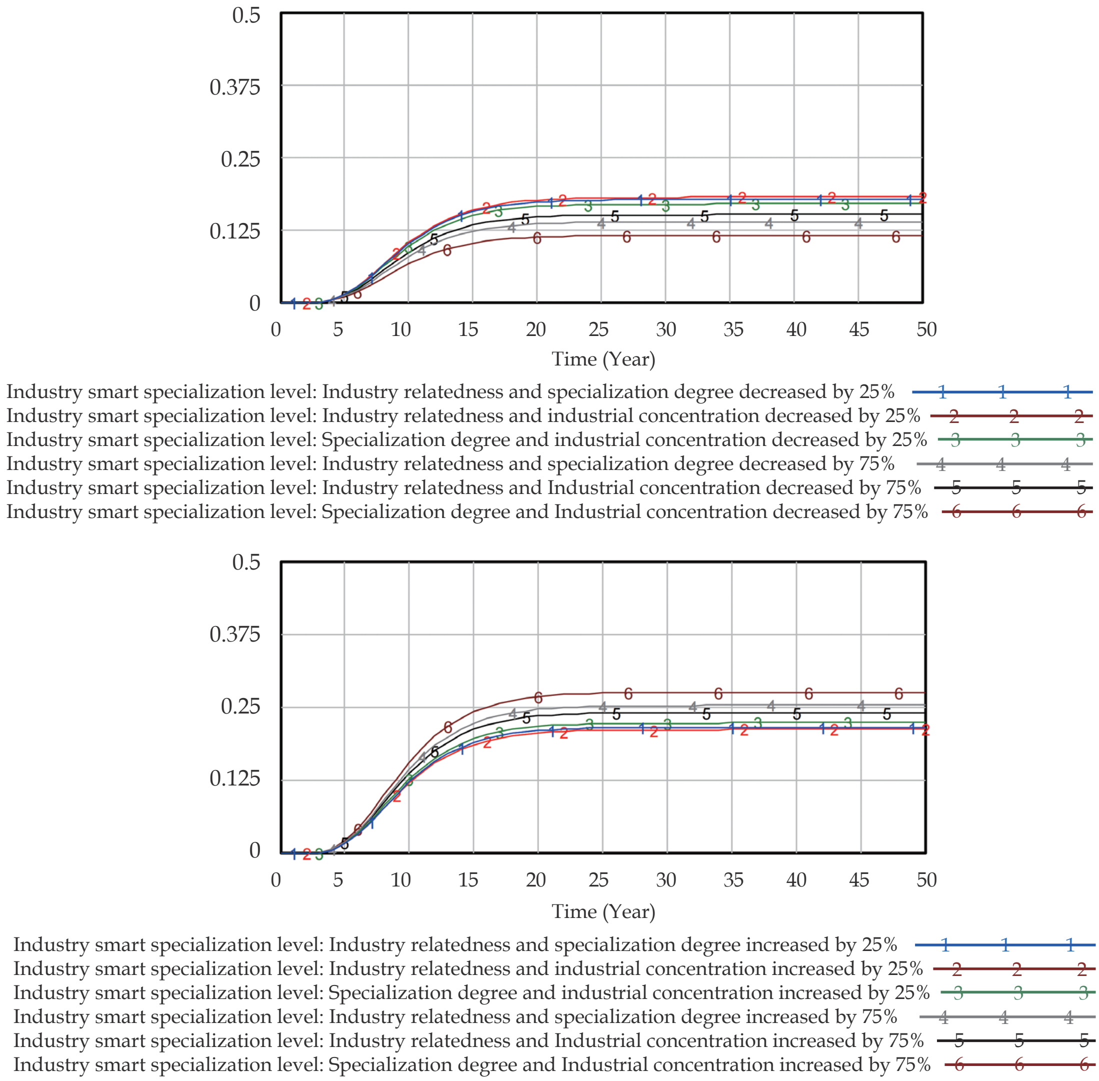

Fig. 21 The level of smart specialization after increasing and decreasing two indicators

The impact of changing each of the three specialization level indicators on the degree of industry smart specialization is shown in Figure 22. The level of industrial smart specialization attains 0.2260 and 0.2862 when the three indicators of industrial relatedness, industrial concentration, and specialization degree are improved by 25% and 75% concurrently. The level of industrial smart specialization attains 0.1653 and 0.1033 when the three indicators of industrial significance, industrial concentration, and specialization degree are dropped by 25% and 75% concurrently.

5.4. Multiple scenario comparison analysis

The multiple scenario comparison analysis includes a combination of simultaneous adjustments to the level of smartness and to the level of specialization.

5.4.1. Increasing the level of smartness and the level of specialization

The impact of simultaneously adjusting the level of industrial smart specialization and the level of industrial specialization is demonstrated in Figure 23. The industry smart specialization level attains 0.3083

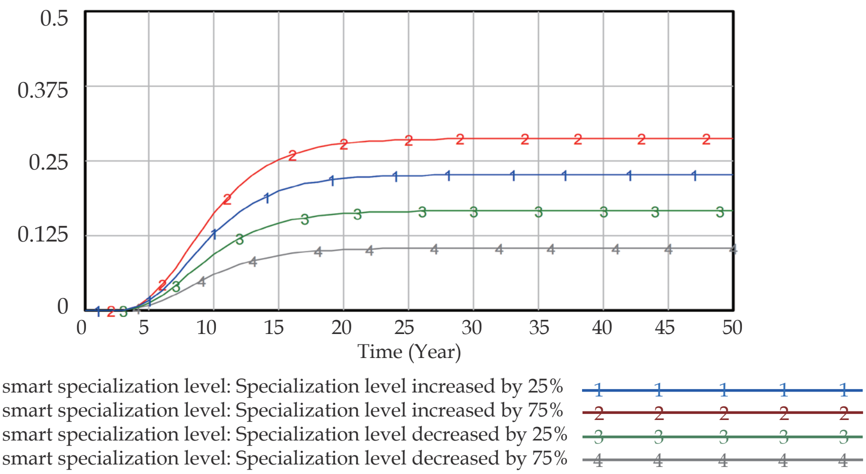

Fig. 22 The level of smart specialization after increasing and decreasing the three indicators

when both the smart level indicator and the specialization level indicator grow by 25%. The industry smart specialization level attains 0.3875 when both the smart level indicator and the specialization level indicator grow by 25%. The industry smart specialization level attains 0.3833 when the smart level indicator rises by 75% and the specialization level indicator rises by 25%. The level of industry smart specialization attains 0.4665 when both the smart level indicator and the specialization level indicator grow by 75%. The industry smart specialization level attains 0.4665 when both the indicator of smart level and the indicator of specialization level both grow by 75%.

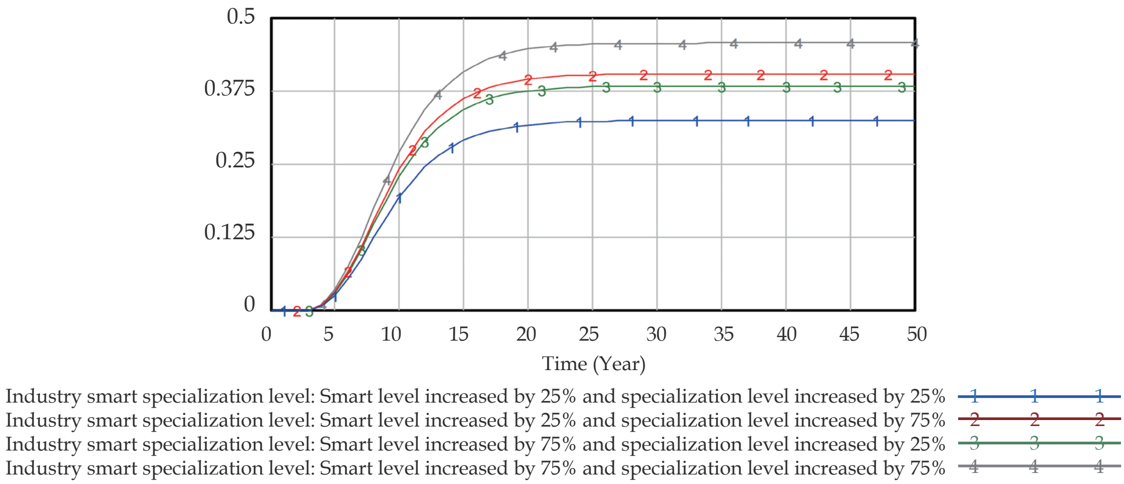

Fig. 23 The level of smartness and the level of specialization increase simultaneously

5.4.2. Increasing the level of smartness and decreasing the level of specialization

The impact of simultaneously adjusting the level of industrial smartness and the level of industrial specialization is displayed in Figure 24. The industry smart specialization level attains 0.2429 when the smart level indicator is elevated by 25% and the specialization level indicator is dropped by 25%. The industry smart specialization level attains 0.1595 when the smart level indicator is raised by 25% and the specialization level indicator is lowered by 75%. The level of industrial smart specialization attains 0.2102 when the smart level rises by 75% and the specialization level falls by 75%.

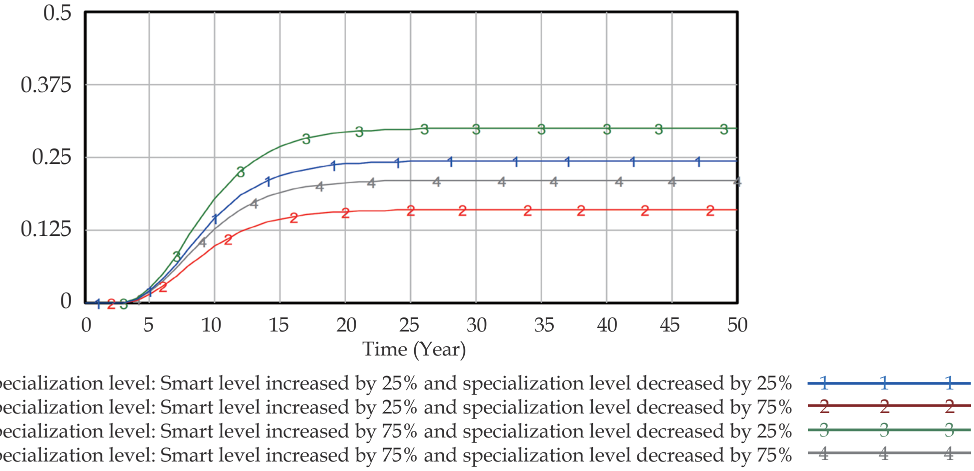

Fig. 24 The level of smartness increases while the level of specialization decreases

5.4.3. Decreasing the level of smartness and increasing the level of specialization

The impact of simultaneously adjusting the indicators of the level of industrial smartness and the level of industrial specialization is illustrated in Figure 25. The industry smart specialization level attains 0.2628 when the smart level indicator is reduced by 25% and the specialization level indicator is increased by 25%. The industry smart specialization level attains 0.3390 when the smart level indicator is reduced by 25% and the specialization level indicator is increased by 75%. The degree of industrial clever specialization attains 0.2672 when the smart level falls by 75% and the specialization level rises by 75%.

5.4.4. Decreasing the level of smartness and the level of specialization

Figure 26 displays the impact on the level of industry smart specialization of simultaneously changing the level of industrial smartness and the level of industrial specialization indicators. The industry smart specialization level attains 0.1864 when both the smart level indicator and the specialization level indicator are reduced by 25%. The industry smart specialization level attains 0.1087 when the smart level indicator is reduced by 25% and the specialization level indicator is reduced by 75%. When the smart level is reduced by 75% and the specialization level is reduced by 75%, the level of industrial smart specialization attains 0.1275.

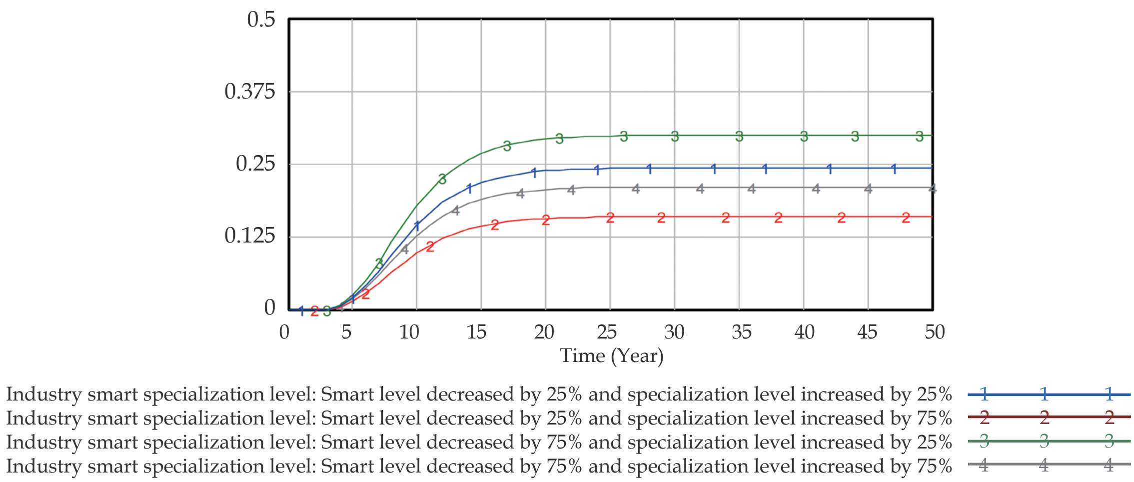

Fig. 25 The level of smartness decreases while the level of specialization increases

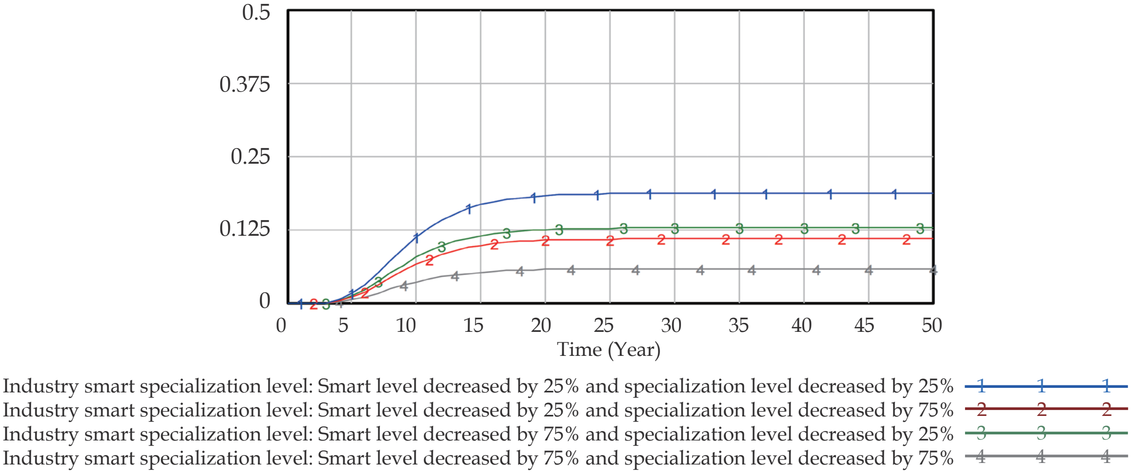

Fig. 26 The level of smartness and the level of specialization decrease simultaneously

6. Main Conclusions and Policy Implications

6.1. Main conclusions

In conjunction with system theory, a system dynamics model of China's manufacturing smart specialization is built, and based on discussing the interaction mechanism of each subsystem, the model is empirically tested by using data from the provinces and municipalities of China's mainland. The evaluation index system of China's regional manufacturing smart specialization level is proposed, and the static evaluation comparison analysis is carried out with the support of the entropy TOPSIS method.

(1) According to the results of the static level evaluation, the smart specialization and coupling levels of China's regional manufacturing industries are growing annually, fluctuating downward, and fluctuating upward, respectively, while the overall level of manufacturing industry smart specialization is declining. The regional manufacturing industry in China exhibits an unbalanced level of development for manufacturing smart specialization; the eastern region's provinces and municipalities have strong development levels, the central region's development levels are improving more quickly, and the western and northeastern regions have weak levels of development for manufacturing smart specialization.

(2) The simulation curve indicates that the growth of the manufacturing smart specialization level follows the "logarithmic index" curve in terms of shape. The level of industrial smart specialization is positively impacted by the level of industrial smartness, specialization and coupling; however, this effect is a "critical scale" in nature. The level of industrial smart specialization increases quickly in the early stage and progressively stabilizes in the later stage.

(3) The evaluation results from the dynamic simulation demonstrate that the level of industrial smart specialization is enhanced by both the smart level indicators and the specialization level indicators. The industrial correlation, industrial concentration, and specialization level within the specialization level indicators have stronger effects on the improvement of the industrial smart specialization level compared to the smart level indicators. The highest level of industrial smart specialization can also be achieved through the application of dynamic policy combinations.

6.2. Policy implications

Enhancing the level of smart specialization is an effective strategy for China's regional manufacturing industry to cope with the international market competition. The regional manufacturing sector in China has clear gradient disparities in the level of smart specialization. The interaction, holistic, and dynamic system influence of the three subsystems, the smart level subsystem, the specialization level subsystem, and the coupling level subsystem on the level of smart specialization, is not the result of the action of a single element. To enhance the regional manufacturing smart specialization system and encourage and maximize the high-quality development of the regional manufacturing sector, different ideas and approaches should be adopted.

(1) The process of enhancing and optimizing the regional manufacturing smart specialization system takes time, and improving the environment and behavior of innovators also require long-term accumulation. Therefore, to encourage the optimization of the industrial innovation system, the primary elements influencing industrial development should be continuously adjusted. The feedback relationship between the components and subsystems of the smart level, specialization level, and coupling system should be fully estimated as part of the process of raising the level of smart specialization in China's manufacturing sector. Additionally, a continuous, dynamic, and combined active intervention strategy system should be established to achieve the highest level of smart specialization in the manufacturing sector.

(2) Pay attention to regional variations and create a regional industrial innovation framework that takes local conditions into account. Based on maximizing the level of the regional industrial innovation system, we should pinpoint the positive aspects of regional development and its key pillars, concentrate on strengthening the regional industry's weaknesses and weak links in the innovation process, maximize its positive aspects, and encourage the advancement of regional industrial innovation and development.

(3) Continually encourage the regional industrial innovation system's endogenous power. To encourage industries and sectors to take the lead in driving regional development, it is important to identify and nurture the endogenous strength of the local industry. A perfect internal innovation network must be created, the symbiotic relationship between regional innovation subjects must be integrated and optimized, the integration of innovation factors and innovation subjects must be encouraged, and innovation subjects must be encouraged to realize more potential and kinetic energy.

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