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Research on the Driving Effect of Innovation Elements on the Digital Transformation of Manufacturing Industry in China under the Moderating Effect of Knowledge Stickiness

——Benchmark mechanisms, moderating effects, and spatial heterogeneity

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***Abstract**: The digital transformation of manufacturing industry cannot be separated from the support of innovative elements, and knowledge stickiness has a moderating effect in the process of acquiring innovative elements. After analyzing the benchmark driving mechanism of innovation elements on the digital transformation of manufacturing industry, this study explores the moderating effect and spatial heterogeneity of knowledge stickiness. Based on the panel data of 28 provinces in China Mainland from 2012 to 2024, this study conducts an empirical test by constructing panel data models. Research has found that innovation elements can significantly drive the digital transformation of the manufacturing industry, and knowledge stickiness has a significant reverse moderating effect in it. The moderating effect of knowledge stickiness exhibits spatial heterogeneity, with an overall difference in the moderating strength of "western>central>northeast>eastern".*

***Keywords**: innovative elements; digital transformation of manufacturing industry; knowledge stickiness;China*

***JEL Classification**:L69;O33.*

I. Introduction

The digital transformation of manufacturing industry is an important part of the deep integration of the digital economy and the real economy, and is an important driving force for China's manufacturing industry to move towards high-end, intelligent, and green development. The digital transformation of manufacturing industry cannot be achieved without the support of innovative elements such as talent, technology, and R&D fund. Innovative elements are important source to ensure that enterprises gain sustained competitive advantages, and thus are the key to realizing the digital transformation of manufacturing industry. The acquisition of innovative elements relies on both self-accumulation and creation, as well as external introduction. In the current context where the innovation foundation of China's manufacturing industry is generally weak, attracting external innovation elements through various policies is the main way for digital transformation of manufacturing industries in various regions. Knowledge stickiness refers to the knowledge transfer obstruction caused by the protection of knowledge owners, weak ability of knowledge receivers to absorb, share, and generate knowledge, or inappropriate knowledge transfer environment [1-2]. The existence of knowledge stickiness poses obstacles to the flow of innovative elements between regions, which in turn hinders the digital transformation of manufacturing industry. In addition, there are differences in the innovation foundation of manufacturing industries in different regions, and the level of knowledge stickiness also varies. When formulating policies for the digital transformation of manufacturing industry, it is necessary to fully consider the spatial differences in knowledge stickiness, which has great practical significance for the effective formulation of relevant policies by local governments.

Ⅱ. Literature Review

The existing studies on the driving force of innovation factors on the digital transformation of manufacturing industry mainly focus on three aspects. Firstly, the direct driving force of innovation factors on the digital transformation of manufacturing industry. Existing studies generally agree that innovation elements can drive the digital transformation of manufacturing [3-5], and mainly focuses on a static perspective. Innovation elements have fluidity and knowledge characteristics, and knowledge stickiness is inevitable in the process of innovation elements transfer, but existing studies has paid less attention to it. The second is the indirect driving force of innovation elements on the digital transformation of manufacturing industry. Some studies suggest that innovation elements such as talent and capital need to rely on factors such as organizational structure and investment channels to drive the digital transformation of manufacturing industry. Innovation elements are important indirect driving factors for the digital transformation of manufacturing industry [6-7]. The third is the spatial spillover of innovative elements driving the digital transformation of manufacturing industry. Some studies have focused on the spatial spillover of innovation elements in driving the digital transformation of manufacturing industry, and believe that innovation elements in a certain region will have an impact on the digital transformation of manufacturing industry in other regions to a certain extent [8-9]. A few studies have considered the issue of knowledge stickiness [1,10], but they mainly focus on empirical research and have not analyzed the mechanism of the regulatory effect of knowledge stickiness. In addition, there are differences in the innovation foundation of manufacturing industries in different regions, and there is spatial heterogeneity in the moderating effect of knowledge stickiness, which has been rarely addressed in existing research.

In order to comprehensively grasp the driving effect of innovation elements on digital transformation of manufacturing industry, from a dynamic perspective, this study analyzes the benchmark driving mechanism of innovation elements on the digital transformation of manufacturing industry, brings knowledge stickiness into the research framework, discusses the moderating effect of knowledge stickiness in the process of innovation elements driving, as well as the spatial heterogeneity mechanism of the moderating effect of knowledge stickiness, and uses the panel data of 28 provinces in China Mainland from 2012 to 2024 to conduct an empirical test. This not only makes up for the current lack of theoretical research, but also has certain practical reference value for government departments to effectively formulate industrial policies from the perspective of innovative elements.

Ⅲ. Hypothesis

3.1 The benchmark mechanism of the innovative elements drive the digital transformation of manufacturing industry

According to the Theory of Industrial Upgrading, industrial upgrading is the process of industrial innovation, and technological factors are the main driving force for promoting industrial upgrading. The essence of the digital transformation of manufacturing industry is to apply advanced digital technology to the manufacturing industry, promote the transformation of manufacturing industry to higher levels, and innovation elements represented by technology are the main driving force for the digital transformation of manufacturing industry. According to the Innovation Theory, innovation is a new combination of various innovative elements such as talent, technological foundation, and funding. Digital transformation is the process of innovation and upgrading in the manufacturing industry, which is the inevitable result of the accumulation of innovative elements such as talent, technological foundation, and capital in the manufacturing field.

Hypothesis 1: Innovation elements can drive the digital transformation of manufacturing industry.

3.2 The moderating effect of knowledge stickiness in the digital transformation of manufacturing driven by innovation elements

The transfer of innovative elements between regions is the main way for the accumulation of innovative elements, and whether innovation elements can be effectively transferred involves three aspects: element subjects (including element owners and element receivers), element transfer environment, and element attributes. According to the Theory of Knowledge Transfer, in the process of knowledge transfer, insufficient willingness of knowledge owners to transfer, weak acceptance ability of knowledge receptors, unsuitable knowledge transfer environment, and strong exclusivity of knowledge can all cause obstacles to knowledge transfer, resulting in knowledge stickiness. The existence of knowledge stickiness hinders the inflow of various innovative elements, which is not conducive to effectively obtaining the required innovative elements in the process of digital transformation of manufacturing industry, and thus regulates the driving role of innovative elements in the digital transformation of manufacturing industry.

Hypothesis 2: Knowledge stickiness has a reverse moderating effect in the digital transformation of manufacturing driven by innovation elements.

3.3 The spatial heterogeneity of knowledge stickiness's moderating effect

According to the Theory of Resource Endowment, there are differences in natural resources, industrial foundation, technological foundation, human resources and other endowments between regions, which directly leads to regional differences in the acceptance ability of innovation element transfer recipients and the environment for innovation element transfer. China has a vast territory, and uneven regional development is an objective reality of the current economic development in China. There are significant differences in industrial foundation, technological foundation, human resource quality, and market-oriented mechanism construction among different regions, resulting in differences in the level of knowledge stickiness between regions. As a result, there is spatial heterogeneity in the moderating effect of knowledge stickiness in the digital transformation of manufacturing driven by innovation elements.

Hypothesis 3: There is spatial heterogeneity in the moderating effect of knowledge stickiness.

IV. Research Design

4.1 Variable settings

4.1.1 Digital transformation level of manufacturing industry (Dig)

The digital transformation of manufacturing industry is specifically reflected in the R&D, produce, marketing and other aspects of enterprises. Based on existing research [12-13], this study constructs an evaluation indicator system for the digital transformation level of manufacturing industry from three dimensions: R&D, Production and marketing (Table 1).

Table 1 Evaluation indicator system for the digital transformation level of manufacturing industry

Dimension	Indicator	Interpretation of indicator	Attribute
R&D	R&D input	Natural logarithm of R&D expenditure in the manufacturing industry of a certain province (10000 yuan)	+
	R&D output	Number of valid invention patents in the manufacturing industry of a certain province （Number）	+
Production	Digitalization of Production	Industrial Internet platform application penetration rate in a certain province (%)	+
		Numerical control rate of key manufacturing processes in a certain province (%)	+
Marketing	Marketing digitalization	Digital penetration rate of business management in a certain province (%)	+
		Number of manufacturing enterprises engaged in e-commerce activities in a certain province (Number)	+
	Digitalization of Services	The average number of websites owned by manufacturing enterprises in a certain	+

	province (Number)

Using the entropy weight method to evaluate the digital transformation level of manufacturing industry and the knowledge stickiness level :

$$Y_{qp}=\begin{cases}\frac{y_{qp}-min(y_{qp})}{max(y_{qp})-min(y_{qp})} & Positive\ attribute\\ \frac{max(y_{qp})-y_{qp}}{max(y_{qp})-min(y_{qp})} & Negative\ attribute\end{cases} \tag{1}$$

$$w_{qp}=\frac{y_{qp}}{\sum_{q=1}^{m}y_{qp}} \tag{2}$$

$$Q_p=\frac{1-E_p}{\sum_{p=1}^{n}(1-E_p)} \tag{3}$$

$$E_p=(\ln m)^{-1}\sum_{q=1}^{m}(w_{qp}\ln w_{qp}) \tag{4}$$

Where, q and p respectively indicate the specific indicators and the research objects, m and n are the number of indicators and objects, y and Y are the original and normalized values of indicators, w and Q are the weights of indicators and objects, and E is the entropy value.

4.1.2 Innovation elements level (Ele)

Human resources, technology, and R&D fund are the main representatives of innovation elements [14-15], measured respectively by the proportion of population with higher education, the proportion of permanent population (%), the natural logarithm of technology market transaction volume (billion yuan), and R&D funding (billion yuan). To characterize the liquidity characteristics of innovation elements, the sum of their periodic change rates is used to measure the level of innovation elements. The higher the value, the higher the overall level of innovation elements, and to some extent, the greater the liquidity of innovation elements.

4.1.3 Knowledge stickiness level (Know)

The knowledge stickiness level depends on factors such as the knowledge subject, knowledge transfer environment, and knowledge attributes. Based on existing research [1,10], this study constructs an evaluation indicators system for knowledge stickiness level from three dimensions: knowledge subject, knowledge transfer environment, and knowledge attributes. The specific indicators for each dimension are shown in Table 2.

Table 2 Evaluation indicators system of knowledge stickiness

Dimension	Indicator	Interpretation of indicator	Attribute
Knowledge subject	Knowledge owner	Number of fresh graduates from universities in a certain province (10000 people)	+
		The proportion of the population with higher education in a certain province to the local permanent population (%)	+
	Knowledge receiver	Number of new product developments in high-tech industries in a certain province (Number)	+

Knowledge attribute	Exclusivity of knowledge	The natural logarithm of the turnover of the technology market in a certain province (billion yuan)	+
		Natural logarithm of the cost of technological transformation in a certain province (billion yuan)	+
	Knowledge complexity	Natural logarithm of external technology introduction expenses in a certain province (billion yuan)	+
		Number of external technology introduction contracts in a certain province (Number)	+
Knowledge transfer environment	Marketization level	Proportion of employment in non-state-owned enterprises to total employment in a certain province (%)	+
	Urbanization level	The proportion of urban population to the total permanent population in a certain province (%)	+

4.1.4 Control variables

In addition to innovation elements and knowledge stickiness, the digital transformation of manufacturing industry will also be affected by other factors. This study sets government fiscal expenditure (*X1*), industrial structure (*X2*), fixed assets investment (*X3*), digital base (*X4*), and openness (*X5*) as control variables, government fiscal expenditure is represented by the proportion of government budget expenditure in nominal GDP, industrial structure is represented by the ratio of output value of the tertiary industry to output value of the secondary industry, fixed assets investment is represented by the natural logarithm of total fixed assets investment, digital base is represented by the natural logarithm of industrial scale of the digital economy, and openness is represented by the natural logarithm of foreign direct investment after the exchange rate of RMB against the US dollar is deflated.

4.2 Models

Construct the following Benchmark model with innovation elements level (*Ele*) as the independent variable and the digital transformation level of manufacturing industry (*Dig*) as the dependent variable:

$$Dig_{it} = \alpha + b_1 Ele_{it} + \sum \varphi_j X_{jit} + \gamma_i \times \phi_t + \mu_{it} \tag{5}$$

Introduce the knowledge stickiness level (*Know*) as a moderating variable into the Benchmark model and construct a Moderation model:

$$Dig_{it} = \alpha + b_1 Ele_{it} + b_2 Know_{it} + b_3 Ele_{it} \times Know_{it} + \sum \varphi_j X_{jit} + \gamma_i \times \phi_t + \mu_{it} \tag{6}$$

Where, α is a constant term, b_1、b_2、b_3、φ_j are the parameters to be estimated, *X* represents the control variable, and *i* and *t* respectively indicate space and time. γ and ϕ are individual fixed effects and time fixed effects, respectively. To avoid endogeneity caused by unobservable variables changing with individuals and time, this study introduces an interaction term between space individual and time individual in the model and fixes it. μ is a random perturbation term.

4.3 Data

The data selects the panel data of 28 provinces in China Mainland from 2012 to 2024 (because the data of Xizang, Xinjiang and Inner Mongolia are seriously missing, it is excluded). The data was collected and organized from the China Science and Technology Statistical Yearbook, the China Industrial Statistical Yearbook, the China Statistical Yearbook, the China Macroeconomic Database, the Statistical Yearbook of each province, as well as CSMAR database. The missing values are supplemented using interpolation, and Winsor(1,99) truncation is applied to all variables. The descriptive statistical indicators of each variable are shown in Table 3.

Table 3 The descriptive statistical indicators

Variable type	Variable	N	Mean	St.d	Min	Median	Max
Dependent variable	*Dig*	364	0.3688	0.2625	0.0862	0.3706	0.6847
Independent variable	*Ele*	364	0.5879	2.3006	-3.6251	0.6011	15.2215
Moderating variable	*Know*	364	0.3412	0.4185	0.1539	0.3388	0.5401
Control variables	*X1*	364	20.7619	4.6626	11.0058	21.9247	33.2017
	X2	364	87.7699	9.6294	18.9207	88.2006	158.6217
	X3	364	2.0415	0.9014	0.5148	2.1003	3.6251
	X4	364	2.7495	0.6251	1.7751	2.9716	4.3628
	X5	364	1.5911	0.8814	0.2218	1.6109	3.0073

V. Empirical testing

5.1 Benchmark effect test

Using the OLS method to estimate the parameters of the Benchmark model, according to benchmark model in Table 4, the regression coefficient of *Ele* is 0.1863, passing the significance level of 1%. The innovation elements level has a significant positive impact on the digital transformation level of manufacturing industry. Hypothesis 1 is true. The regression coefficients of each control variable are positive, but there are differences in significance levels. *X1*, *X2*, and *X4* are significant at least at the 10% level, indicating that government fiscal expenditure, industrial structure, and digital base have a significant positive impact on the digital transformation levlel of manufacturing industry. However, *X3* and *X5* failed to pass the 10% significance level, and fixed assets investment and openness have no significant positive impact on the digital transformation level of manufacturing industry.

Table 4 Estimation results of the Benchmark model and the Moderation model

Variable	Benchmark model	Moderation model
α	0.0281(0.6284)	0.0106(0.2184)
Ele	0.1863^{***}(3.2018)	0.0227^{***}(2.7745)
Know		-0.0332^{***}(-2.9153)
$Ele \times Know$		-0.1573^{***}(-2.8844)
X1	0.0707^{*}(1.8695)	0.0573^{*}(2.1562)
X2	0.0083^{**}(2.3152)	0.0105^{***}(2.9654)

X3	0.0044(1.6954)	0.0028(0.5287)
X4	0.0186**(2.7628)	0.0211***(3.6284)
X5	0.0038(1.0055)	0.0072(1.3617)
$\gamma \times \phi$	√	√
R^2	0.3847	0.4153
F-statistics	165.6284	184.9054
p值	0.0000	0.0000

Note: *, **, *** respectively indicate that the t-test is significant at the 10%, 5%, and 1% levels; √ represents fixed effects. (Same as below)

5.2 Moderation effect test

From the estimation results of the Moderation model in Table 4, it can be found that, the regression coefficient of *Know* is -0.0332, reaching a significance level of 1%. Knowledge stickiness has a significant reverse direct impact on the digital transformation level of manufacturing industry, which lays the foundation for the reverse regulatory effect of knowledge stickiness. The regression coefficient of $Ele \times Know$is -0.1573 at the 1% level, indicating that the interaction term between knowledge stickiness and innovation elements has a significant reverse impact on the digital transformation level of manufacturing industry. And at this time, the *Ele* regression coefficient is significantly 0.0227 at the 1% level, which is significantly lower than the 0.1863 in Benchmark model. The addition of knowledge stickiness weakens the positive impact of innovation elements on the digital transformation level of manufacturing industry. Therefore, knowledge stickiness has a significant reverse regulatory effect in the process of digital transformation of manufacturing industry driven by innovation elements. Hypothesis 2 holds true.

5.3 Spatial heterogeneity test

According to the division of China's economic regions by the China National Bureau of Statistics, 28 provinces in China Mainland are divided into four regions: the eastern (Beijing, Tianjin, Hebei, Shanghai, Jiangsu, Zhejiang, Fujian, Shandong, Guangdong, Hainan), the central (Shanxi, Anhui, Jiangxi, Henan, Hubei, Hunan), the northeast (Liaoning, Jilin, Heilongjiang), and the western (Guangxi, Chongqing, Sichuan, Guizhou, Yunnan, Shaanxi, Gansu, Ningxia, Qinghai). The sample data from four regions are used to fit the Moderation model. As shown in Table 5, there are significant differences in the regression coefficients among different regions. The regression coefficient in the western is -0.2085, which is significant at the 1% level and has the highest absolute value among all regions. The reverse adjustment of knowledge stickiness in the process of digital transformation of manufacturing industry driven by innovation elements is greatest in the western. The regression coefficient in the central region is significantly -0.1803 at the 1% level, with an absolute value second only to the eastern. Knowledge stickiness also has a strong reverse moderating effect in the central region. The regression coefficients in the northeast and eastern are -0.1006 and -0.0863, respectively, both significant at the 1% level. The reverse moderating effect of knowledge stickiness is relatively small in the northeast and eastern, with the smallest reverse moderating effect in the eastern. Hypothesis 3 holds true.

Table 5 Summary of spatial heterogeneity test results

Variable	Eastern	Central	Northeast	Western
α	0.0083(0.6395)	0.0142(1.2017)	0.0217(0.9374)	0.0029(1.0057)
Ele	0.0362***(3.0172)	0.0109***(3.2015)	0.0281***(2.8631)	0.0075**(2.5630)
$Know$	-0.0089**(-2.2452)	-0.0288***(-2.6693)	-0.0142**(-2.4482)	-0.0371***(-2.7755)
$Ele \times Know$	-0.0863***(-2.7251)	-0.1803***(-2.9372)	-0.1006***(-3.1222)	-0.2085***(-3.5214)
$X1$	0.0359**(2.6639)	0.0207**(2.3004)	0.0188***(3.3624)	0.0693***(3.2047)
$X2$	0.0052**(2.2227)	0.0184***(3.2014)	0.0243***(2.5927)	0.0089***(3.9625)
$X3$	0.0120(1.4280)	0.0076(0.9365)	0.0054(1.2044)	0.0106(0.3922)
$X4$	0.0090***(2.7222)	0.0168***(3.0092)	0.0307***(3.7628)	0.0259***(2.9264)
$X5$	0.0088**(2.1544)	0.0115***(2.6932)	0.0041**(2.0051)	0.0185***(2.9625)
$\gamma \times \phi$	√	√	√	√
R^2	0.3862	0.4041	0.3475	0.4226
F-statistics	224.6638	148.3927	250.7715	178.6295
p值	0.0000	0.0000	0.0000	0.0000

5.4 Robustness test

Change the estimation method to SYS-GMM method and re estimate the Moderation model with national and regional data to test the robustness of the empirical conclusions. As shown in Table 6, at the national level, the regression coefficient of *Ele* is significantly 0.0109 at the 1% level, indicating that innovation elements have a significant positive impact on the digital transformation of the manufacturing industry. At the 1% level, the regression coefficient of *Know* is significantly -0.0253, and the regression coefficient of $Ele \times Know$ is significantly -0.1209. Knowledge stickiness has a significant reverse moderating effect on the digital transformation of manufacturing industry driven by innovation factors. This is consistent with the estimated conclusion in Table 4. From different regions, the regression coefficients in each region have passed the significance level of 1%, and the absolute values of the regression coefficients in the four regions show a regional difference state of "western>central>northeast>eastern". This is consistent with the estimated conclusion in Table 5. Overall, the empirical conclusions of this study have high robustness.

Table 6 Summary of robustness test results

Variable	National	Eastern	Central	Northeast	Western
α	0.0223	0.0169	0.0055	0.0339	0.0123
	(0.6941)	(1.1006)	(0.8541)	(0.1522)	(0.6226)
Ele	0.0109***	0.0266***	0.0088***	0.0193***	0.0045**
	(2.9365)	(3.3965)	(2.8174)	(3.9965)	(2.2625)

$Know$	-0.0253***	-0.0137***	-0.0213**	-0.0176***	-0.0296**
	(-3.2006)	(-2.8632)	(-2.3004)	(-3.7545)	(-2.4444)
$Ele \times Know$	-0.1209***	-0.0362***	-0.1284***	-0.0588***	-0.1722***
	(-3.6214)	(-3.5214)	(-3.9654)	(-2.8475)	(-4.2001)
$X1$	0.0406**	0.0317*	0.0186*	0.0174***	0.0557***
	(2.3141)	(2.0074)	(1.8547)	(2.9554)	(2.6924)
$X2$	0.0131**	0.0061***	0.0195***	0.0218**	0.0144***
	(2.3521)	(2.9514)	(2.6514)	(2.0066)	(3.3214)
$X3$	0.0075	0.0133	0.0058	0.0082	0.0124
	(0.9654)	(1.1524)	(0.6954)	(1.5145)	(0.7744)
$X4$	0.0186***	0.0074***	0.0133***	0.0264***	0.0217***
	(2.5517)	(3.2014)	(2.8768)	(3.1155)	(2.7541)
$X5$	0.0091***	0.0105**	0.0069***	0.0078***	0.0163**
	(2.8866)	(2.3624)	(3.1452)	(3.2081)	(2.4433)
$\gamma \times \phi$	√	√	√	√	√
R^2	0.3905	0.3625	0.4112	0.3956	0.3362
p 值(F-stat)	0.0000	0.0000	0.0000	0.0000	0.0000
p 值[AR(1)]	0.0069	0.0021	0.0108	0.0093	0.0051
p 值[AR(2)]	0.0836	0.1007	0.1373	0.0951	0.1436
Hansen	0.2051	0.1836	0.2307	0.1666	0.1909

VI. Conclusion and Suggestions

6.1 Conclusions

The digital transformation of manufacturing industry cannot be separated from the support of innovative elements such as human resources, technology, and R&D funds. Knowledge stickiness has a moderating effect in the process of acquiring innovative elements. Studying the driving mechanism of innovative elements on the digital transformation of manufacturing industry, as well as the moderating effect of knowledge stickiness in it, has high theoretical and practical significance for effectively formulating policies to drive the digital transformation of manufacturing industry from the perspective of innovative elements. Research has found that:

(1) Innovation elements can significantly drive the digital transformation of manufacturing industry.

(2) Knowledge stickiness has a significant reverse moderating effect on the digital transformation of manufacturing driven by innovation elements.

(3) The moderating effect of knowledge stickiness exhibits spatial heterogeneity, with an overall difference of "western>central>northeast>eastern".

6.2 Recommendations

To effectively promote the digital transformation of manufacturing industry in China, local governments of China can formulate relevant policies from the perspective of strengthening local innovation elements, such as:

(1) Pay attention to the accumulation of innovative elements. While strengthening the construction of local digital infrastructure, local governments can encourage local manufacturing enterprises to invest in their own digital technology application and innovation, digital talent cultivation, and other aspects through professional training, tax incentives, and other means. While accumulating innovative elements within the region, it can also effectively enhance the local manufacturing industry's ability to undertake external innovative elements from the perspective of knowledge receptors, thereby promoting the digital transformation of the local manufacturing industry.

(2) Establish a mechanism for introducing external innovative elements. Local governments can optimize institutional construction and guarantee measures in areas such as high-level talent treatment, property rights protection, and credit, and pay special attention to the construction of policies for introducing innovative elements such as technological innovation, talent introduction, and research and development funds at the level of manufacturing enterprises. They can formulate preferential policies and reward mechanisms for innovative elements of manufacturing enterprises, and build external innovation element introduction mechanisms at the regional macro and enterprise levels.

(3) Optimize the intellectual property trading market environment. Government departments need to provide a comprehensive legal protection system for the transfer of innovative elements in institutional construction, strengthen the construction and enforcement of intellectual property regulations, and establish a legal and compliant intellectual property trading market mechanism. At the same time, the government fully respects the market rules of intellectual property transactions. Government should minimize direct intervention in intellectual property transactions and use indirect methods such as guidance and incentives to regulate intellectual property transactions, attract external innovative elements to flow into the local area, and optimize the local intellectual property trading market environment.

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