

Article

Do Industrial Support Policies Help Overcome Innovation Inertia in Traditional Sectors?

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Abstract

Enhancing innovation capability can effectively promote the development of traditional industries. Based on Lewin's behavioral model theory, this study investigated the relationship between industrial support policies and innovation behavior within traditional industries. Utilizing survey data collected from 152 traditional industrial enterprises in 2024 and employing structural equation modeling, the main findings are as follows: Industrial support policies can effectively alleviate the "innovation inertia" of traditional industries, with all policies being significant at the 1% confidence level. Among them, policies related to industry–university–research cooperation platforms have the most significant impact, with a standardized coefficient of 0.941, followed by fiscal and taxation policies (standardized coefficient: 0.846) and financial policies (standardized coefficient: 0.729). Innovation motivation acts as a mediating mechanism between industrial policies and innovation behavior. Industrial support policies accelerate the conversion of reserve-oriented patent portfolios into practical applications, helping to break through patent barriers and effectively alleviate innovation inertia. Consequently, the government should prioritize improving public services, and policy formulation needs to be oriented towards enhancing innovation efficiency. While ensuring industrial security, it is advisable to moderately increase competition to guide traditional industry market players towards thriving in competitive environments.

Keywords: policy instruments; innovation inertia; traditional industries



Academic Editor: Tsutomu Harada

Received: 6 June 2025

Revised: 12 July 2025

Accepted: 14 July 2025

Published: 17 July 2025

Citation: Liu, H., & Zhou, Y. (2025). Do Industrial Support Policies Help Overcome Innovation Inertia in Traditional Sectors? *Economics*, 13(7), 206. <https://doi.org/10.3390/economics13070206>

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1. Introduction

Against the backdrop of promoting industrial upgrading through scientific and technological innovation, the transformation and upgrading of traditional industries hold significant importance. The concept of "traditional industries" is relative, typically referring to a range of industries retained from the previous stage of industrialization following a period of rapid growth. These industries are predominantly labor-intensive and capital-intensive. The Third Plenary Session of the 23rd Central Committee of the Communist Party of China emphasized the need to "use national standards to lead the optimization and upgrading of traditional industries, and support enterprises in transforming and upgrading traditional industries using digital intelligence technologies and green technologies." For many years, government innovation policies have consistently emphasized their role in enhancing the innovation capabilities of traditional industries. Studies have shown that government R&D subsidies, when coupled with the commercialization of advanced R&D outcomes, lead to significant knowledge spillover effects from the R&D activities of traditional industries into the technological progress of emerging industries. However, the behavioral inertia of government intervention has fostered a business environment

for manufacturing enterprises characterized by agglomeration and reliance on low-cost competition. This “greenhouse effect” inclines firms’ technological innovation models towards the lower end of the spectrum, resulting in “innovation inertia”, a phenomenon observed in industrial development. Innovation inertia indicates how traditional industries exhibit strong path dependence in their development models, finding it difficult to relinquish established core advantages and resources—such as specific technologies and equipment, stable market demand, and supply chains. As a result, the transformative and innovative capabilities of traditional industries gradually weaken. The causes of innovation inertia may stem from the influence of monopolistic factors on enterprise technology. They may also arise from the effects of sunk costs, economies of scale, and vested interests, which solidify production modes and supply relationships, thereby restricting the entry of more efficient firms. Furthermore, innovation inertia is prevalent in numerous resource-intensive industries, where resource abundance fosters resource dependence and exerts a crowding-out effect on technological innovation.

Traditional industries, characterized by their diversity, massive scale, extensive market reach, and substantial output value, constitute the foundation of a modern industrial system and play an indispensable role in industrial and supply chains. Without traditional industries, many emerging and future industries would struggle to achieve full circularity, potentially leading to “supply chain fragmentation”. The CPC Central Committee Decision on Further Comprehensively Deepening Reform and Advancing Chinese Modernization emphasizes establishing institutional mechanisms for developing new-quality productive forces based on local conditions, stating that “The transformation and upgrading of traditional industries also constitutes developing new quality productive forces.” Furthermore, the Guidelines on Accelerating the Transformation and Upgrading of Traditional Manufacturing, issued by the Ministry of Industry and Information Technology (MIIT) and seven other ministries, explicitly advocate innovation-driven development, ascending to the mid-to-high end of global value chains, accelerating the adoption of advanced applicable technologies, persistently optimizing industrial structures, and implementing industrial foundation re-engineering projects. Accelerating this transformation enhances supply chain resilience, safeguards industrial and supply chain security, achieves industrial structure optimization, and constructs a modern industrial ecosystem. Examining whether China’s industrial and innovation policies can mitigate innovation inertia in traditional industries is therefore critical for enhancing the effectiveness of industrial policy.

In view of this, based on the survey data of 152 traditional industrial enterprises, this study employs structural equation modeling to evaluate whether industrial policies can effectively promote innovation in traditional industries and examines the mediating mechanism of innovation motivation. The marginal contributions of this study are as follows:

First, innovation motivation significantly affects the transformation of innovation achievements in traditional industries. Enterprises are the main players in innovation, and different innovation motivations have varying impacts on enterprises’ patent transformation. In the future, innovative achievements made to cater to the government for policy support will be unfavorable for transformation; however, patents used to prevent infringement, suppress competitors, or accumulate technical reserves can help enterprises achieve technical market locking. Meanwhile, such patents have high market value and can be transformed effectively. Second, industrial support policies provide an objective factual basis from an innovation behavior perspective, thus playing a positive role in improving innovation inertia in traditional industries. Among them, public service policies, such as training and introducing professional talents, establishing industry–university–research innovation cooperation platforms, and promoting the sharing of instruments and equipment, test sites, and other resources, have the most significant impact, followed by fiscal

and taxation policies and financial policies. Third, industrial support policies demonstrate the highest innovation efficiency in driving the transformation of patents motivated by preventing infringement, suppressing competitors, or accumulating technical reserves. On one hand, such policies can help standard incumbents break through patent barriers, thereby overcoming “active innovation inertia” and shifting away from the previous incremental upgrading model. On the other hand, they can empower non-standard incumbents to pursue innovation: by gaining insights into existing innovation outcomes while sustaining the accumulation of heterogeneous innovation resources, these enterprises can work toward overcoming “passive innovation inertia.” Fourth, this study enriches the literature on traditional industries. Unlike previous research focusing on strategic emerging industries and “specialized, sophisticated, distinctive, and novel” industries, this study takes traditional industries as its starting point to explore the relationship between China’s innovation incentive policy tools and innovation behaviors in traditional industries, thereby contributing to the existing literature.

2. Literature Review

2.1. Conceptual Dimensions and Formation Mechanisms of Innovation Inertia

The concept of “innovation inertia” was first proposed by Moore, who established a core–periphery analytical framework to study this phenomenon (Moore, 1993). The core theoretical premise classifies business operations into two categories based on whether they generate differential competitive advantages: core activities and peripheral activities. The relative proportion of these activities within an enterprise determines its degree of innovation inertia. This inertia manifests through diminished innovation intentionality, compromised innovation quality, rigid innovation modalities, and attenuated innovation capacity. Innovation inertia can be categorized into functional inertia and dysfunctional inertia. Dysfunctional inertia occurs when innovation agents consciously recognize environmental changes yet resist adaptation because of entrenched practices, manifesting primarily as diminished innovation intentionality (Bandura, 1978). Functional inertia arises when innovation agents engage in innovative activities without recognizing contextual shifts, resulting in outputs that fail to reflect environmental demands, primarily evident in innovation outcomes (Teece, 1986). Multiple factors contribute to innovation inertia, including industrial agglomeration (Ohtake, 2023), technological lock-in (Rajneesh, 2002), path dependency in innovation trajectories (Dosi, 1982), and insufficient innovation incentives.

2.2. Policy Instruments and Innovation Inertia

Lee and Malerba argue that industrial technology catch-up in late-developing countries is a process where enterprises, in response to specific windows of opportunity, formulate effective strategic responses through connections and interactions with sectoral innovation systems (Lee & Malerba, 2017). They identify three key variables for industrial catch-up in late-developing countries, namely, opportunity, strategy, and innovation system. Since Solow first proposed a method to measure the contribution of technological progress to economic growth and attributed the unexplained portion of per capital output growth (after deducting the net growth in capital and labor) to technological progress, the driving factors of technological innovation have become a research focus (Solow, 1956). The two most representative hypotheses to have emerged are “technology push” and “demand pull”, and if both driving forces are to coexist, the active role of the government is required. On this basis, governments need to encourage innovation through two approaches, namely, reducing innovation costs via “technology push policies” and increasing the returns of successful innovations through “demand pull policies,” which form the “government attraction” dynamic hypothesis (Nemet, 2009).

Policy tools exert multifaceted influences on innovation behavior through leverage effects, crowding-out effects, and signaling mechanisms. To counteract innovation inertia, governments deploy various interventions—subsidies, grants, and fiscal incentives—aiming to stimulate innovation intentionality and cultivate preferences for high-end innovation (Xiao & Jiang, 2013). However, empirical findings diverge regarding industrial policy efficacy in mitigating innovation inertia. For instance, industrial agglomeration—a primary development model promoted by local governments—often fosters organizational rigidity (Hannan & Freeman, 1984) and isomorphic structures (DiMaggio & Powell, 1983). This institutional environment incentivizes firms to pursue imitable process innovations while neglecting novel product/service R&D, culminating in policy-induced innovation inertia (Tao et al., 2013). Hu Bin and his colleagues categorized firms' innovation preferences into two archetypes: high-end innovation, which involves the simultaneous pursuit of product and process innovation, and low-end innovation, which exclusively focuses on process innovation. Their analysis of manufacturing agglomerations revealed that behavioral inertia (North, 1990) in government intervention fosters ecosystems dependent on low-cost competition (Moore, 1993). This institutional environment precipitates the dominance of low-end innovation patterns and entrenches innovation inertia. Moreover, information asymmetry in governmental subsidy allocation cultivates policy dependency, incentivizing firms to engage in rent-seeking and preferential policy exploitation. This strategic gaming manifests as “strategic innovation”—prioritizing quantifiable outputs over substantive quality, thereby reinforcing the quantity/quality trade-off (Ahuja & Lampert, 2001) dilemma in corporate innovation. On the contrary, attention should be paid to enterprises' strategies for coping with institutional limitations, and it is proposed that enterprises can either attempt to reform the existing institutional environment or seek alternative institutional arrangements in other regions to meet their technological needs (Rajneesh, 2002).

2.3. Pathways for Traditional Industry Transformation

China's traditional industries exhibit substantial technological gaps compared to advanced economies. Currently positioned to leverage latecomer advantages, these industries demonstrate statistically significant productivity gains through exogenous technological progress driven by imitative innovation. Conversely, endogenous progress via indigenous innovation shows no statistically significant improvement in technological advancement levels. Technological innovation constitutes the fundamental pathway for upgrading traditional industries (Zheng & Zhang, 2022). Through scientific and technological innovation, the inherent path dependency of traditional industries can be overcome, enabling multidimensional development. For instance, integrating high technologies can transform traditional industries into strategic emerging industries or transition them towards sunrise industries characterized by low pollution and energy consumption. The innovation-driven process is realized through three synergistic phases: front-end driving, mid-end driving, and back-end driving, as well as the simultaneous realization of these three phases (Gereffi, 1999). These phases exhibit spatial coexistence and temporal succession, with their synchronization intensifying and inter-phase intervals shortening progressively.

3. Methodology

3.1. Research Design

This study employs a quantitative research approach, first identifying behavioral patterns of the target population through questionnaire surveys and then providing an in-depth exploration of causal relationships among patent application motivations, policy instruments, and patent commercialization behaviors using structural equation modeling (SEM), thereby overcoming the limitations of singular methodological approaches.

3.2. Variable Selection

As a crucial means for the state to regulate the macro-economy, industrial policies have become significant external factors influencing industry development. To address market failures, governments encourage or restrict the development of specific industries through industrial policies. Industrial support policies can be categorized into fiscal, tax, financial, and public service policies. Based on traditional industrial innovation demand policies and drawing on the content of the China Patent Investigation Report 2023 regarding policy support for patent industrialization, this study focuses on three major policy tools, namely, tax, financial, and public service policies, defined as follows:

Tax policy tools: Represented by tax reduction and fee exemption policies, conditional on patent industrialization.

Financial policy tools: Represented by measures to strengthen guidance on intellectual property pledge financing, venture capital, and other related activities.

Public service policies: Cultivation and introduction of professional talent; establishment of industry–university–research (IUR) innovation cooperation platforms; and promotion of resource sharing for equipment, testing facilities, and experimental sites.

Based on the existing scholarly research and the two main survey components regarding the primary purposes of enterprise patent applications, combined with the survey objects, the following three items were designed based on a five-point Likert scale:

“What types of policy support are needed to promote the industrialization of enterprise patents?”—This represents the demand level of traditional industry patent behaviors for policy tools.

“What do you consider to be the motivations behind your enterprise’s patent acquisition?”—This represents different motivational types for enterprise patent acquisition.

“The contribution of patent transformation to the enterprise’s profit margin is high.”—This represents the efficiency of patent transformation. The contents of the relevant variables are shown in Table 1.

Table 1. Variable definitions.

Variable Category	Variable Name	Symbol	Measurement Items	Variable Type	Scale/Value Range
Industrial Support Policy	Talent Cultivation and Introduction	G1	“Cultivate and introduce professional talents”	Independent	5-point Likert scale (1 = not important at all~5 = extremely important)
	Tax Incentives for Patent Commercialization	G2	“Tax reduction and exemption policies conditional on patent commercialization”	Independent	
	Industry–University–Research Collaboration Platform	G3	“Establish industry–university–research innovation cooperation platforms”	Independent	
	Resource Sharing Policy	G4	“Promote the sharing of equipment, testing facilities, and experimental sites”	Independent	
	Intellectual Property Financing Support	G5	“Strengthen guidance on intellectual property pledge financing, venture capital, etc.”	Independent	
Patent Application Motivation	Qualification and Assessment	M1	“For assessment, enterprise qualification certification, project application, or title evaluation”	Independent	
	Corporate Image Building	M2	“Shape corporate image and enhance publicity effects”	Independent	
	Prevent Infringement, Deter Competitors, or Accumulate Technology Reserves	M3	“Prevent infringement, suppress competitors, or accumulate technology reserves”	Independent	
	Licensing and Transfer for Profit	M4	“Achieve economic benefits through licensing or transferring patents”	Independent	
	Patent Commercialization	M5	“Realize patent commercialization”	Independent	
Profit Contribution of Patent Transformation	Profit Margin Contribution	P	“The contribution of patent transformation to the enterprise’s profit margin is high”	Independent	

Table 1. *Cont.*

Variable Category	Variable Name	Symbol	Measurement Items	Variable Type	Scale/Value Range
Patent Transformation	Transformation Behavior	T	“Whether the patent has been transformed internally or externally” (0 = no transformation; 1 = transformed)	Dependent	Binary variable (0/1)

3.3. Data Sources

This study primarily focuses on the relationship between policy incentives and innovation behaviors in traditional industries, such as mining, electricity, heat, gas, water production and supply, and manufacturing, where the main business entities are state-owned enterprises. Innovation behaviors in traditional industries are proxied by patent-related activities, including using patent application motivations to substitute for innovation willingness and patent transformation behavior indicators to substitute for innovation outcomes. Given that the required data on patent behaviors cannot be retrieved from public databases or statistical records, a questionnaire survey method was employed for data collection. The complete questionnaire can be found in Appendix A.

This study’s sampling frame is defined as large-scale state-owned enterprises in 2024 that belong to the category of traditional manufacturing industries (including mining, electricity, heat, gas, water production and supply, and manufacturing) and have been established for more than 5 years. This study adopted a combination of stratified random sampling and targeted invitation to recruit sample enterprises. Enterprises in the sampling frame were divided into four layers according to industry, with 25% of enterprises randomly selected from each layer, resulting in a total of 300 enterprises (75 from each layer). Relevant personnel of the enterprises were contacted by distributing both paper and electronic questionnaires. The response rate of this survey was as follows: 300 enterprises were initially invited, with 152 effectively participating. The actual effective response rate, calculated as the proportion of the final sample size to the initial sampling frame, is approximately $152/1200 \approx 12.7\%$, which is consistent with the general response level of surveys on traditional industrial enterprises. As Joseph F. Hair Jr. noted, when the number of influencing factors falls within a reasonable range (e.g., 7), the minimum sample size should be 150. The sample size in this study thus meets the requirement for the research question.

The questionnaire included 4 latent variables (patent application motivation, patent transformation policy tools, patent transformation behavior, patent transformation efficiency) and 12 observed variables, measured using a five-point Likert scale. The respondents were asked to use numbers from 1 to 5 to indicate their agreement with the statements, where the numbers represent the following:

- 1 = Completely disagree;
- 2 = Disagree;
- 3 = Uncertain;
- 4 = Agree;
- 5 = Completely agree.

3.4. Descriptive Statistics

The high proportion of middle-to-senior management (91%) ensures that the respondents have direct involvement in strategic decisions related to patent applications and transformation. Additionally, over one-third of the respondents (35.53%) have more than 10 years of tenure, with 59.35% having worked in their companies for 3–10 years. This long-term employment experience equips them with in-depth knowledge of the enterprise’s patent practices, policy environments, and operational details. These demographic

characteristics collectively demonstrate that the respondents are well-qualified to provide accurate insights into their companies' patent behaviors, thereby enhancing the credibility and reliability of the survey data.

The valid enterprise samples obtained from the survey, when classified by industry category, reveal that mining enterprises account for the highest proportion, at 58.4%, followed by enterprises in electricity, heat, gas, and water production and supply, at 18.10%, and manufacturing enterprises, at 13.6%. This questionnaire can effectively reflect the basic situation of traditional industries.

The survey shows that patent output and internal patent usage exhibit a U-shaped pattern. In the past three years, enterprises applying for 1–10 patents accounted for 54.5%, while those applying for more than 60 patents represented 21.7%. Regarding the proportion of patents used internally, 71.10% of the enterprises have an internal utilization rate below 30%, and 12.5% have a utilization rate of 76% or higher. The data reveal that both the patent application volumes and internal transformation rates of enterprises show a U-shaped trend—most enterprises have low application volumes and low transformation rates, but a small number have both high application volumes and high internal usage rates. In terms of internal and external transformation, internal is the primary mode. Descriptive statistical information of the samples is shown in Table 2.

Table 2. Descriptive statistics.

Name	Option	Frequency	Percentage (%)	Cumulative Percentage (%)	Name	Option	Frequency	Percentage (%)	Cumulative Percentage (%)
Identity	Intellectual Property Managers	2	1.32	1.32	Average annual sales or operating income in the past 3 years	0–200	13	8.55	8.55
	Middle and Senior Managers	138	90.79	92.11		201–2000	9	5.92	14.47
	Administrative Support Staff	2	1.32	93.42		2001–10,000	3	1.97	16.45
	Others	4	2.63	96.05		10,001–30,000	9	5.92	22.37
	Technical Engineers	6	3.95	100.00		More than 30,000	118	77.63	100.00
Tenure	Less than 1 year	13	8.55	8.55	Number of patents applied for by the enterprise in the past 3 years (unit: piece)	1–10	83	54.61	54.61
	1–3 years	35	23.03	31.58		11–30	19	12.50	67.11
	3–5 years	40	26.32	57.89		30–60	17	11.18	78.29
	6–10 years	10	6.58	64.47		More than 60	33	21.71	100.00
	More than 10 years	54	35.53	100.00	The proportion of patents used for self-purpose in the total number of patents	Less than 30%	108	71.10	71.1
The proportion of professional and technical personnel in the enterprise to the total number of full-time employees	Less than 20%	50	32.89	32.89		31–50%	20	13.20	84.2
	21–50%	75	49.34	82.24		51–75%	5	3.30	87.5
	51–80%	10	6.58	88.82		More than 76%	19	12.5	100
	More than 80%	17	11.18	100.00	The proportion of patents converted externally to the total number of patents	Less than 30%	138	90.8	90.8
Industry	Mining	75	49.3	49.3		31–50%	10	6.6	97.4
	Manufacturing	29	19.1	68.4		51–75%	3	2	99.3
	Electricity, Heat, Gas, and Water Production and Supply	32	21.1	89.5		More than 76%	1	0.7	100
	Others	16	10.5	100					
					Total	152	100.0	100.0	100

3.5. Model Specification

Based on the previous analysis, the factors influencing patent behavior are numerous, and their measurement is highly subjective; they are difficult to directly quantify, and the relationships among them are complex. This study therefore employed structural equation modeling (SEM) for measurement and analysis, whereby SEM was used to describe the

relationships between explanatory and explained variables among latent variables. In this context, it was applied to estimate the causal relationships among patent application motivations, policy tools, and patent transformation behaviors. The SEM framework consists of two components: the measurement model, which assesses the relationship between latent variables and observed indicators, and the structural model, which examines the causal relationships among latent variables themselves.

The measurement model characterizes latent variables by selecting indicator variables and describes the relationship between latent variables and indicator variables. Since both patent application motivation and policy tools are reflective latent variables (i.e., the direction of causal influence is from the latent variable to the indicator variables), the measurement models for these two latent variables can both be specified as reflective types. Taking the explanatory latent variable patent application motivation as an example, its measurement model is expressed as in Equation (1):

$$Y = \Lambda\eta + \varepsilon \quad (1)$$

Equation (1) demonstrates that a single factor “patent application motivation” (η) is measured by a five-dimensional indicator vector Y , which includes the following:

- y_1 : Evaluation and assessment, and enterprise qualification certification;
- y_2 : Project application, professional title evaluation, or corporate image building and promotional effects;
- y_3 : Prevent infringement, deter competitors, or accumulate technology reserves
- y_4 : Economic benefits achieved through licensing or transfer;
- y_5 : Patent industrialization.

Here, Λ represents the factor loading coefficients between each measurement indicator variable and the latent variable being explained (η), while ε denotes the measurement error of the latent variable.

This study, therefore, first tested the reliability and validity of the measured latent variables. Reliability measures the degree of measurement error and evaluates the extent to which a measurement method is free from random and unstable errors. A scale reliability coefficient above 0.9 indicates excellent reliability, while a coefficient below 0.7 suggests some items need to be discarded. Using the SPSSAU software program for analysis, the reliability test results show that the coefficient for patent support policies is 0.931, and the coefficient for patent application motivation is 0.75, indicating that these indicators pass the reliability test.

Validity assesses whether a comprehensive evaluation system can accurately reflect the evaluation objectives and requirements, referring to the correctness of the measurement tool’s characteristics. Higher validity means the measurement results better reflect the characteristics to be measured. The KMO values for all variables are greater than 0.8, indicating good partial correlation among variables. The result from Bartlett’s test of sphericity is less than 0.05, rejecting the sphericity hypothesis and confirming significant correlations among the original variables at the 1% level, which is suitable for further analysis. The reliability statistics are presented in Table 3. KMO and Bartlett’s test are presented in Table 4.

Table 3. Reliability statistics.

Variable	Cronbach’s Alpha	Standardized Cronbach’s Alpha	Number of Items
Patent Application Motivation	0.753	0.750	5
Industrial Support Policies	0.928	0.931	5

Table 4. KMO and Bartlett’s test.

KMO Sampling Adequacy Measure		0.851
Bartlett’s Test of Sphericity	Approximate Chi-square	1003.609
	Degrees of Freedom (df)	66
	Significance	0.000

To detect potential common method bias in the questionnaire, Harman’s Single-Factor Test was conducted via an exploratory factor analysis (EFA). The results showed that the variance explained by the first factor was 39.178%, which is below the threshold of 40%. Additionally, there was no dominant factor (i.e., the variance explained by multiple factors was relatively balanced), indicating a low risk of common method bias. The analysis results are presented in Table 5.

Table 5. Table of variance explanation rates.

Factor Number	Eigenvalue		
	Eigenvalue	Variance Explained (%)	Cumulative (%)
1	6.268	39.178	39.178
2	2.615	16.344	55.522
3	1.433	8.958	64.480
4	1.213	7.578	72.058
5	0.809	5.059	77.116
6	0.800	4.997	82.114
7	0.507	3.167	85.281
8	0.384	2.397	87.678
9	0.376	2.350	90.028
10	0.346	2.162	92.190
11	0.293	1.831	94.021
12	0.261	1.630	95.651
13	0.229	1.434	97.084
14	0.190	1.187	98.271
15	0.143	0.895	99.166
16	0.133	0.834	100.000

The structural model describes the relationships between latent explanatory variables and latent explained variables, and can also be used to estimate the causal relationships between various latent variables. Taking the core framework (as mentioned above) that characterizes the influence relationships among patent transformation behavior, patent application motivation, and industrial support policies as an example, this study has constructed the following structural model:

$$\eta = \gamma_1 \xi_1 + \gamma_2 \xi_2 + \zeta \quad (2)$$

In Equation (2), η represents the explained latent variable “patent transformation behavior”. The latent variable “patent support policies” is measured by five indicator variables: the cultivation and introduction of professional talent; tax reduction and fee exemption policies conditional on patent industrialization; the construction of industry–university–research innovation cooperation platforms; the promotion of resource sharing for equipment and testing sites; and intellectual property pledge financing and venture capital activities. Another latent variable (“patent application motivation”) is measured using five indicator variables: evaluation and assessment, and enterprise qualification certification; project application, professional title evaluation, or other purposes, and corporate

image building and promotional effects; infringement prevention, competitor suppression, or technological reserve accumulation; economic benefits through licensing/transfer; and patent industrialization. γ_1 and γ_2 represent the influence coefficients of policy tools and patent application motivation on patent transformation behavior, respectively, with ζ denoting the prediction error.

4. Results

4.1. Benchmark Regression Estimation Results

4.1.1. Policy Instruments, Patent Application Motivation, and Patent Transformation Behavior

- Industrial policy support has a positive promoting effect on the innovation behavior of traditional industries. Table 6 presents the regression results of the three structural models.

In Structural Model 1, the regression coefficient of the latent variable “policy instruments” on patent transformation behavior is significantly positive at the 5% level, with a magnitude of 0.227. This indicates that the stronger the policy support, the more patent transformation behaviors occur in traditional industries: a one-unit increase in policy instruments will lead to a 22.7% increase in patent transformation behavior.

- Innovation motivation has a significant impact on innovation behavior.

In Structural Model 2, the regression coefficient of the latent variable “patent application motivation” on patent transformation behavior is significant at the 5% level, with a value of 0.331. This suggests that the stronger the patent application motivation, the more frequent the patent transformation behaviors: a one-unit increase in patent application motivation will lead to a 33.1% increase in patent transformation behavior.

- Patent application motivation plays a mediating role between industrial support policies and patent transformation behavior.

In Structural Model 3, when simultaneously verifying the impacts of policy instruments and patent application motivation on patent transformation, the patent transformation policy instruments show no significant effect on patent transformation behavior, while the influence coefficient of patent application motivation on patent transformation is 0.372. This indicates that a one-percentage-point increase in patent application motivation leads to a 37.2% improvement in patent transformation behavior. As an external environment factor affecting patent transformation behavior, the insignificant effect of patent transformation policy instruments contradicts Lewin’s behavioral model theory and the existing research.

Table 6. Regression results of structural models.

Variable	Structural Model 1	Structural Model 2	Structural Model 3
Industrial Support Policies	0.227 ** (0.020)		0.087 (0.500)
Patent Application Motivation		0.331 ** (0.010)	0.372 ** (0.010)

Note: The values in parentheses are *t*-values, ** represent significance levels of 5% respectively. The same applies to the following tables.

4.1.2. Regression Results of Measurement Models

- Among policy instruments, public policies have the most significant impact on innovation in traditional industries, followed by fiscal and taxation policies and financial policies. The regression results of the measurement models are presented in Table 7.

In Model 1, among policy instruments, public policies have the most significant impact on innovation in traditional industries, followed by fiscal and taxation policies and financial policies. Specifically, G3 (building industry–university–research innovation cooperation platforms) has the largest standardized regression coefficient of 0.941, indicating that policies supporting industry–university–research innovation cooperation platforms have the greatest influence on patent transformation behavior in traditional industries; G1 (policies for cultivating and introducing professional talent) has a standardized regression coefficient of 0.881, reflecting a high demand for professional talent in patent transformation in traditional industries—the introduction of such talent can enable the transformation of existing patents; G4 (promoting the resource sharing of equipment, testing sites, etc.) has a standardized regression coefficient of 0.868, suggesting a strong policy demand for experimentation and pilot testing in traditional industries; G2 (tax and fee reduction policies conditional on patent industrialization) has a standardized regression coefficient of 0.848, indicating that the demand of traditional industry enterprises for special tax and fee reduction policies is weaker than for policies related to talent and platforms; and G5 (intellectual property pledge financing, venture capital, etc.) has the smallest standardized regression coefficient of 0.728 among all policy instruments. This not only indicates the low demand for policies related to intellectual property pledge and venture capital but also reflects the low awareness in traditional industries for using financial tools for innovation, as none of the surveyed enterprises have introduced venture capital for technological innovation.

In traditional industries, motivations such as preventing infringement, suppressing competitors, and accumulating technological reserves exert the strongest influence on patent transformation behavior. In contrast, reputational motivations, as well as those related to evaluation, assessment, and project application, have the weakest impact on such behavior.

The coefficient of M3 motivation (preventing infringement, suppressing competitors, or accumulating technological reserves) is 0.791 (the largest among all); the coefficient of M4 motivation (achieving economic benefits through licensing or transfer) is 0.647, and that of M5 motivation (realizing patent industrialization) is 0.637, indicating that motivations for internal and external transformation determine transformation behavior. The coefficient of M2 (building corporate image and forming promotional effects) is 0.625, suggesting that non-market motivations have a stronger impact on patent transformation than market motivations, while the coefficient of M1 (evaluation and assessment, enterprise qualification certification, project application, professional title evaluation, or other purposes) is 0.388.

- Patent application motivation mediates the relationship between industrial support policies and patent transformation behavior.

When verifying the impacts of policy instruments and patent application motivation on patent transformation simultaneously, the patent transformation policy instruments show no significant effect on patent transformation behavior, while the influence coefficient of patent application motivation on patent transformation is 0.166; this indicates that a one-percentage-point increase in patent application motivation leads to a 16.6% improvement in patent transformation behavior. As an external environmental factor influencing patent transformation behavior, the insignificant impact of patent transformation policy instruments runs counter to Lewin's behavioral model theory and existing literature. This discrepancy indicates that the mediating effect of patent application motivation between industrial support policies and patent transformation behavior merits consideration.

Table 7. Regression results of measurement models.

Variable		Measurement Model 1	Measurement Model 2	Measurement Model 3
Industrial Support Policies	G1	0.881 *** (0.000)		0.882 *** (0.000)
	G2	0.850 *** (0.000)		0.848 *** (0.000)
	G3	0.941 *** (0.000)		0.941 *** (0.000)
	G4	0.868 *** (0.000)		0.868 *** (0.000)
	G5	0.728 *** (0.000)		0.729 *** (0.000)
Patent Application Motivation	M1		0.388 ** (0.000)	0.642 *** (0.000)
	M2		0.625 *** (0.000)	0.854 *** (0.000)
	M3		0.791 *** (0.000)	0.636 ** (0.000)
	M4		0.647 *** (0.000)	0.412 *** (0.000)
	M5		0.637 *** (0.000)	0.352 *** (0.000)

Note: The values in parentheses are *t*-values; *** and ** represent significance levels of 1% and 5%, respectively. The same applies to the following tables.

4.2. Mediating Effect Test

Patent application motivation fully mediates the relationship between patent transformation policy instruments and patent behavior. When the mediating effect was not considered, policy instruments significantly influenced patent transformation behavior at the 5% confidence level. After introducing patent application motivation as a mediating variable, policy instruments significantly influenced patent application motivation at the 1% confidence level, patent application motivation significantly influenced patent transformation behavior at the 1% confidence level, and the influence of policy instruments on patent transformation behavior became insignificant. This indicates that patent policies have a significant impact on enterprises' patent application motivation. Specifically, policy awareness encourages enterprises to apply for patents to obtain policy support or meet policy requirements. It also suggests that patent policies formulated without considering patent application motivation have a minimal impact on patent transformation behavior. The results of the mediating effect test are shown in Table 8.

Path Coefficient Analysis of Patent Application Motivation as a Mediating Variable on Patent Transformation Behavior.

The standardized regression coefficient of M2 (motivation to build corporate image and form promotional effects) is 0.854, indicating that under the influence of various policies, patents motivated by shaping corporate image and publicity effects are successfully transformed and applied. The coefficient of M1 (motivation to apply for patents for evaluation purposes) is 0.642, which indicates that with policy support, patents applied for evaluation purposes can undergo transformation. This implies that under industrial support policies, innovative patents originally not intended for marketization by enterprises are successfully transformed. The standardized regression coefficient of M3 (strategic motivation, such as preventing infringement and accumulating technological reserves) is 0.636, indicating that strategic motivations have a moderate impact on patent transformation

under policy influence. Patent application motivations oriented toward marketization (M4: achieving economic benefits through licensing/transfer; M5: patent industrialization) show weaker effects on patent transformation. This is because market-oriented enterprises inherently initiate transformation voluntarily: because of their commercial nature, they pay close attention to market demands in patent technology transformation, rationally evaluating “achievements” that cannot bring commercial benefits and avoiding blind patent applications. Consequently, policies have limited driving effects on patents already intended for marketization.

Table 8. Mediating effect test.

Pathway	Effect	Unstandardized Coefficient	Standardized Coefficient
Policy instruments → Patent application motivation → Patent transformation behavior	Total Effect	0.452 *** (0.000)	0.472 *** (0.000)
	Direct Effect	0.166 *** (0.010)	0.366 *** (0.010)
	Indirect Effect	0.037 (0.502)	0.085 (0.502)
Policy instruments →Patent transformation behavior	Total Effect	0.112 ** (0.020)	0.227 ** (0.020)
	Direct Effect	0.112 ** (0.020)	0.227 ** (0.020)
	Indirect Effect	/	/

Note: The values in parentheses are *t*-values; *** and ** represent significance levels of 1% and 5%, respectively. The same applies to the following tables.

Path Coefficients of Policy Instruments on Patent Application Motivation in Traditional Industries.

Among policy instruments, public service policies have the greatest impact on patent application motivation. Specifically, the coefficient of G3 (policy for constructing industry–university–research collaboration platforms) is 0.941, indicating that policies promoting such platforms significantly enhance patent application motivation. Industry–university–research collaboration improves enterprises’ high-quality innovation capabilities by facilitating the sharing of information, knowledge, and technology among collaborators. The path coefficients of G1 (policy for cultivating and introducing professional talent) and G4 (policy for promoting shared access to equipment and testing facilities) are 0.882 and 0.870, respectively, reflecting the strong influence of human capital and capital investment policies on patent application motivation. These coefficients are higher than those of G2 (tax reduction and fee exemption policies conditional on patent industrialization, 0.846) and G5 (intellectual property pledge financing, venture capital, etc., 0.729), suggesting that special policies targeting human capital and fixed asset investment are more effective in stimulating patent application motivation, while financial subsidies, such as tax relief, have weaker effects. The results of the structural equation modeling (SEM) path analysis of mediating effects are shown in Table 9. The path analysis diagram of the mediating effect in the structural equation model is shown in Figure 1.

Table 9. Structural equation modeling (SEM) path analysis of mediating effects.

Variable		Unstandardized Coefficient	Standardized Coefficient
Patent Application Motivation	M1	1.000 (0.000)	0.643 *** (0.000)
	M2	1.428 *** (0.000)	0.854 *** (0.000)
	M3	1.107 *** (0.000)	0.636 *** (0.000)
	M4	0.718 *** (0.000)	0.412 *** (0.000)
	M5	0.606 *** (0.000)	0.352 *** (0.000)
Industrial Support Policies	G1	1.000 (0.000)	0.882 *** (0.000)
	G2	0.938 *** (0.000)	0.846 *** (0.000)
	G3	1.108 *** (0.000)	0.941 *** (0.000)
	G4	0.994 *** (0.000)	0.870 *** (0.000)
	G5	0.950 *** (0.000)	0.729 *** (0.000)

Note: The values in parentheses are *t*-values; *** represent significance levels of 1% respectively. The same applies to the following tables.

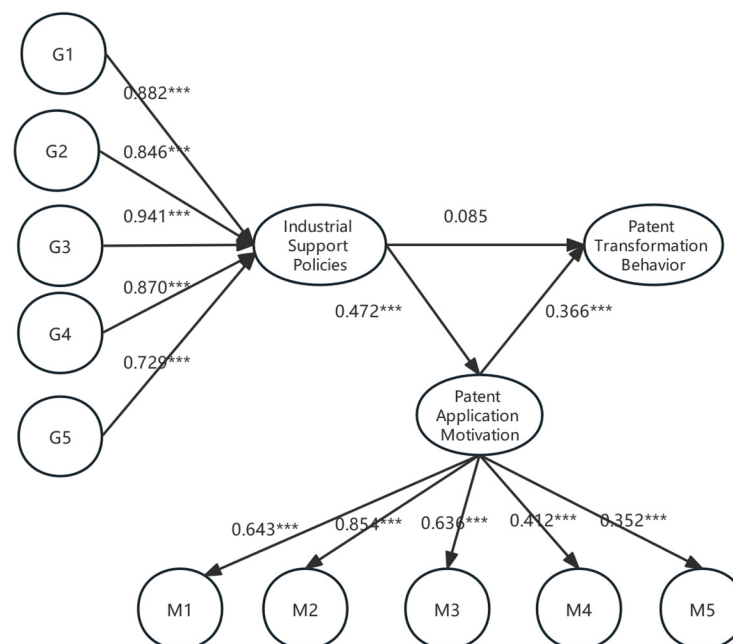


Figure 1. Diagram of Path Analysis for Mediating Effects in Structural Equation Modeling. Note: The values in parentheses are *t*-values; *** represent significance levels of 1%, respectively. The same applies to the following tables.

5. Discussion

Since Solow first proposed a method for measuring the contribution of technological progress to economic growth and attributed the growth in per capita output (Solow, 1956)—after deducting the net growth in capital and labor—to technological progress, the driving factors of technological innovation have become a research hotspot. The “technology push” and “demand pull” hypotheses have emerged as the two most representative frameworks

(Nemet, 2009). When both drivers are required to coexist, the active role of the government becomes essential, based on which governments are called upon to adopt two approaches to encourage innovation, namely, reducing innovation costs through “technology push policies” and increasing the return on innovation success through “demand pull policies,” thus forming the “government gravity” hypothesis of innovation drivers. This study uses survey data obtained from 152 traditional industry enterprises and employs structural equation modeling to test whether industrial policies effectively promote innovation in traditional industries, with innovation motivation examined as a mediating mechanism. The marginal contributions of this study are as follows:

First, industrial support policies play a role in improving the “innovation inertia” of traditional industries and provide objective empirical evidence from the perspective of innovative behavior. Industrial support policies can effectively alleviate innovation inertia in traditional industries, among which public service policies, such as cultivating and introducing professional talent, building industry–university–research innovation cooperation platforms, and promoting the sharing of resources like equipment and testing facilities, have the most significant impact, followed by fiscal and taxation policies and financial policies.

Second, innovation motivation mediates the relationship between industrial support policies and innovative behavior, but market-oriented innovation motivation is less influenced by industrial support policies. Regarding patent transformation behavior, the impact of innovation motivation decreases in the following order: reputation motivation, qualification evaluation motivation, strategic reserve motivation, licensing/transfer motivation, and industrialization motivation. In terms of patent transformation efficiency, the influence of innovation motivation decreases as follows: strategic reserve motivation, reputation motivation, licensing/transfer motivation, industrialization motivation, and qualification evaluation motivation.

Third, this study enriches the literature on traditional industries. Unlike previous research focusing on strategic emerging industries or specialized and sophisticated industries, this study takes traditional industries as the entry point to discuss the relationship between China’s innovation incentive policy tools for traditional industries and their innovation activities, thereby expanding the existing academic discourse.

The next research direction is to conduct a comparative analysis after investigating high-tech industries.

6. Conclusions and Policy Implications

The upgrading and transformation of traditional industries play a critical role in enhancing the resilience and competitiveness of China’s industrial and supply chains, fostering new-quality productivity, and driving high-quality economic development. Based on survey data from traditional industry enterprises, this study uses patent-related behavioral indicators to measure innovation activities in traditional industries and empirically analyzes the effects of policy instruments on patent application motivations and patent transformation behaviors. The main conclusions are as follows:

- Innovation Motivation Significantly Influences the Transformation of Innovation Achievements in Traditional Industries.
- The data analysis shows that patent motivations effectively affect enterprises’ patent transformation behaviors. The motivation to prevent infringement, suppress competitors, or accumulate technological reserves has the greatest impact; market-oriented motivations, such as achieving economic benefits through licensing/transfer and patent industrialization follow, and motivations, like building corporate image, meeting evaluation requirements (e.g., enterprise qualification certification, project appli-

cation, professional title evaluation), and other purposes, have the smallest impact. This indicates that strategic innovations aimed at “catering to” government policies have limited effects on patent transformation. In contrast, patents driven by motivations such as preventing infringement, suppressing competitors, or accumulating technological reserves tend to function as a means of technological locking in the market. Characterized by high quality and market value, such patents are more readily transformable. Public Industrial Support Policies More Effectively Promote the Transformation of Innovation Achievements in Traditional Industries.

Among various industrial support policies, those supporting industry–university–research (IUR) innovation cooperation platforms have the largest impact on patent transformation behaviors in traditional industries, followed by policies for cultivating and introducing professional talent. This reflects the strong demand for specialized personnel in traditional industries to drive patent transformation, as talent introduction enables the implementation of existing patents. Traditional industries also have a strong need for policies promoting shared access to equipment and testing facilities for experiments and pilot trials. In contrast, tax reduction and fee exemption policies conditional on patent industrialization are less effective than other public policies, while intellectual property pledge financing and venture capital policies have the weakest effects. This indicates that traditional industries have limited awareness of using financial tools for innovation and lower policy demand in this regard.

- Industrial Support Policies Achieve the Highest Innovation Efficiency by Stimulating Patent Transformation Driven by Infringement Prevention, Competitor Suppression, or Technological Reserve Motives.

The locking effect of technical standards amplifies the gap between incumbents and non-incumbents, with patent barriers being one manifestation of technological locking. Guided by market profit margins, industrial support policies can effectively promote the transformation of patents motivated by infringement prevention, competitor suppression, or technological reserve accumulation. On one hand, this breaks down patent barriers, urging incumbent standard-setters to overcome “active innovation inertia” and shift from incremental upgrades to more radical innovation. On the other hand, it enables non-incumbents to innovate based on existing achievements while accumulating heterogeneous innovative resources, thus overcoming “passive innovation inertia.” Additionally, this mechanism effectively leverages the spillover effects of technological innovation to drive the overall upgrading of traditional industries.

Based on the above conclusions, the following policy implications are drawn:

- Design Industrial Support Policies with Innovation Motivation as the Core to Overcome Innovation Inertia.

When formulating industrial support policies, governments should comprehensively understand the innovation motivations of traditional industries and prioritize them as the starting point. Policies should aim to genuinely support innovation rather than incentivize “strategic” innovations that merely cater to policy requirements, thereby alleviating the “active innovation inertia” in traditional industries.

Particular attention should be paid to patents motivated by infringement prevention, competitor suppression, or technological reserve accumulation. These patents not only help break the technological standard advantages of patent holders and foster breakthrough innovations beyond incremental upgrades but also dismantle patent barriers, enabling non-incumbent firms to leverage existing technologies effectively, realize spillover effects of innovation in traditional industries, and accumulate heterogeneous resources.

Industrial support policies should prioritize efficiency over quantity, shifting the focus from “quantity-oriented” to “quality- and effect-oriented” innovation. Evaluation indicators for policy outcomes should emphasize the effectiveness of scientific and technological achievement transformation rather than mere patent quantity. Otherwise, low-quality strategic patents may undergo inefficient transformation, yielding limited impacts despite superficial effectiveness.

For market-oriented patent motivations, industrial policies should avoid excessive intervention and fully leverage enterprises’ role as the main drivers of innovation.

- **Strengthen Public Service Policies to Support Innovation in Traditional Industries.**

Among various industrial support policies, public service policies are more effective than fiscal and financial policies in promoting technology transfer in traditional industries. Therefore, efforts should be made to achieve the following:

Expand Industry-University-Research (IUR) Collaboration Platforms: Traditional industries are confronted with both technological path dependence and the dilemma of having the desire to transform yet lacking the capability. IUR collaboration platforms can address technological bottlenecks by integrating the technical and talent advantages of research institutions with enterprises’ market-oriented R&D capabilities, driving joint technological breakthroughs.

Enhance Professional Talent Development: Traditional industries struggle to attract talent compared to high-tech sectors. Policies should combine “talent recruitment” and “talent cultivation,” offering preferential treatments in social security and compensation to attract highly skilled and composite talent. Multi-stakeholder training mechanisms—such as IUR cooperation, mentoring programs, and vocational training—should be promoted to facilitate workforce transformation within industries.

Support Pilot Test Platforms: Pilot testing is critical for bridging R&D and production. Policies should encourage leading enterprises to build industry-wide pilot platforms to upgrade upstream and downstream capabilities while establishing public pilot service institutions with advanced facilities, equipment, and professional teams to provide full-chain, high-level services.

- **Introducing Competition Mechanisms While Safeguarding National Economic Security.**

To achieve innovation-driven development, it is essential to introduce competitive mechanisms—particularly by exposing administrative monopolies to market competition. Economists argue that most technological innovations are passive and reactive; only a minority of enterprises proactively innovate without external competitive pressure. To compel traditional industries to innovate actively and improve efficiency, competition must be intensified while ensuring national economic security. Increased market competition forces traditional players to actively monitor market dynamics and seek profit opportunities to survive.

For administrative monopolies, reforms should focus on separating government functions from enterprise management, distinguishing public ownership from operational control, implementing franchise systems, and strengthening government oversight. Concurrently, an institutional environment conducive to high-quality development in the non-public sector must be fostered. This includes improving market access, policies, legal frameworks, and social support for private and foreign-funded enterprises to enhance their vitality and creativity.

Furthermore, the innovation evaluation system must shift from “emphasizing superficial metrics” to “prioritizing real-world impact.” Governments should move beyond assessing enterprises solely based on patent quantity or conversion rates. Instead, a multidimensional evaluation framework—developed collaboratively by governments, firms,

industry associations, and academia—should balance quantitative and qualitative outcomes. Such a system must not only monitor industrial innovation but also serve as a strategic guide, incentivizing high-quality scientific and technological advancements with tangible applications.

7. Limitations and Future Research

This study examines the impact of industrial support policies on the innovation capability of traditional industries and the mediating mechanism, but there is still room for improvement. In terms of data comprehensiveness, because of the convenience of data collection, the current research mainly focuses on state-owned enterprises, without fully considering non-state-owned enterprises. On the other hand, the industries studied are mainly concentrated in traditional sectors, such as mining, electricity, heat, gas, water production and supply, and manufacturing, with no coverage of other industries.

In future research, we can further explore the impact of industrial support policies on the innovation capability of non-state-owned enterprises and other traditional industries.

Author Contributions: Conceptualization, Y.Z.; methodology, Y.Z.; validation, H.L.; formal analysis, H.L.; investigation, H.L.; data curation, H.L.; writing—original draft preparation, H.L.; writing—review and editing, Y.Z.; funding acquisition, Y.Z. All authors have read and agreed to the published version of the manuscript.

Funding: The Fundamental Research Funds for the Central Universities: 2023JBWB001; the National Social Science Fund of China: 24BJY018.

Institutional Review Board Statement: Not applicable.

Informed Consent Statement: Informed consent was obtained from all subjects involved in the study.

Data Availability Statement: The data of this study cannot be shared due to privacy concerns.

Conflicts of Interest: The authors declare no conflict of interest.

Appendix A

Questionnaire on the Impact of Industrial Support Policies on Improving the Innovation Capability of Traditional Industries

Dear Sir/Madam,

This study aims to analyze the role of industrial support policies in improving the innovation capability of traditional industries and explore countermeasures to enhance such capability. Your opinions are of great significance to this research, and we kindly ask you to spend a few minutes completing this questionnaire. This survey is for academic research purposes only. All data will be kept confidential without your permission, and the content of the questionnaire will not involve your company's trade secrets. Please fill it out objectively. If you are interested in the analysis results, please provide your email address, and we will send the research findings to you promptly upon completion of the study. Thank you again for your support!

We wish you every success in your work and all the best!

Appendix A.1. Personal Basic Information

1. Your gender: ()
A. Male B. Female
2. Your age: ()
A. Under 30 years old B. 31–40 years old C. 41–50 years old
D. 51–60 years old E. Over 60 years old

3. Your education level: ()
A. Junior college B. Bachelor's degree
C. Master's degree D. Doctoral degree E. Other
4. Your position: ()
A. Intellectual property manager B. Middle and senior management
C. Administrative support staff D. Other E. Technical engineer
5. As of October 2024, how long have you been in your current position? ()
A. Less than 1 year B. 1–3 years
C. 3–5 years D. 6–10 years E. More than 10 years
6. Do you have a technical title? ()
A. Yes B. No
7. Your technical title level: ()
A. Primary B. Intermediate C. Senior
8. Do you hold any patents? ()
A. Yes B. No
9. The number of patents you hold: ()
A. 1–3 B. 4–6 C. 6–10 D. More than 10

Appendix A.2. Basic Information of the Enterprise

1. The industry in which the enterprise's main business operates: ()
A. Agriculture, forestry, animal husbandry, and fishery
B. Mining
C. Manufacturing
D. Electricity, heat, gas, and water production and supply
E. Construction
F. Wholesale and retail
G. Transportation, storage, and postal services
H. Accommodation and catering
I. Information transmission, software, and information technology services
J. Financial industry
K. Real estate
L. Leasing and business services
M. Scientific research and technical services
N. Water conservancy, environment, and public facilities management
O. Resident services, repair, and other services
P. Education
Q. Health and social work
R. Culture, sports, and entertainment
S. Public management, social security, and social organizations
2. The type of your enterprise: ()
A. High-tech enterprise
B. Technology giant enterprise
C. Technology-based small and medium-sized enterprise
D. General enterprise
E. Other
3. The time since the enterprise was founded: ()
A. 3 years or less
B. 4–6 years
C. 7–10 years

- D. 10–20 years
E. More than 20 years
4. The number of regular employees in the enterprise: ()
A. 500 or less
B. 501–2000
C. 2001–10,000
D. More than 10,000
 5. The proportion of professional and technical personnel among regular employees: ()
A. Less than 20% B. 20–50%
C. 51–80% D. More than 80%
 6. The average annual sales revenue or operating income of the enterprise in the past 3 years (Unit: RMB 10,000): ()
A. 0–200 B. 201–2000
C. 2001–10,000 D. 10,001–30,000 E. More than 30,000
 7. The proportion of R&D investment in operating income: ()
A. Less than 1% B. 1–3%
C. 3–6% D. More than 6%
 8. The number of patent applications filed by the enterprise in the past 3 years: ()
A. 1–10 B. 11–30
C. 30–60 D. More than 60
 9. The proportion of applied or externally licensed patents among the applied patents: ()
A. Less than 30% B. 30–50%
C. 50–75% D. More than 75%
 10. The proportion of patent purchase amount in R&D expenses: ()
A. Less than 10% B. 10–30%
C. 31–50% D. More than 50%
 11. The proportion of self-used patents in the total number of patents: ()
A. 30% or less B. 31–50%
C. 51–75% D. More than 76%
 12. The proportion of externally transformed patents in the total number of patents: ()
A. 30% or less B. 31–50%
C. 51–75% D. More than 76%

Appendix A.3

Table A1. Industrial Support Policies and Industrial Innovation (Please Tick ☐ the Score That Matches Your Opinion).

Questionnaire Content	Score (Very Little Effect ← → Very Significant Effect)				
	Completely inconsistent	Slightly consistent	Neutral	Basically consistent	Completely consistent
1. What are the motives for innovation?					
Qualification and Assessment	1	2	3	4	5
Corporate Image Building	1	2	3	4	5
Prevent Infringement, Deter Competitors, or Conduct Technology Reserves	1	2	3	4	5
Licensing and Transfer for Profit	1	2	3	4	5
Patent Commercialization	1	2	3	4	5
2. What government policy support is needed to improve the innovation capability of traditional industries?	Completely inconsistent	Slightly consistent	Neutral	Basically consistent	Completely consistent

Table A1. Cont.

Questionnaire Content	Score (Very Little Effect ← → Very Significant Effect)				
	1	2	3	4	5
Talent Cultivation and Introduction	1	2	3	4	5
Tax Incentives for Patent Commercialization	1	2	3	4	5
Industry–University–Research Collaboration Platform	1	2	3	4	5
Resource Sharing Policy	1	2	3	4	5
Intellectual Property Financing Support	1	2	3	4	5
3. Patent conversion methods	Completely inconsistent	Slightly consistent	Neutral	Basically consistent	Completely consistent
Self-investment for implementation and transformation	1	2	3	4	5
Cooperative implementation	1	2	3	4	5
Patent assignment	1	2	3	4	5
Patent licensing	1	2	3	4	5
Valuation for equity participation	1	2	3	4	5
4. The efficiency and effectiveness of patent conversion are very high.	1	2	3	4	5

References

- Ahuja, G., & Lampert, C. M. (2001). Entrepreneurship in the large corporation: A longitudinal study of how established firms create breakthrough inventions. *Strategic Management Journal*, 22, 521–543. [\[CrossRef\]](#)
- Bandura, A. (1978). Self-efficacy: Toward a unifying theory of behavioral change. *Advances in Behaviour Research and Therapy*, 1(4), 139–161. [\[CrossRef\]](#)
- DiMaggio, P. J., & Powell, W. W. (1983). The iron cage revisited: Institutional isomorphism and collective rationality in organizational fields. *American Sociological Review*, 48, 147–160. [\[CrossRef\]](#)
- Dosi, G. (1982). Technological paradigms and technological trajectories: A suggested interpretation of the determinants and directions of technical change. *Research Policy*, 11(3), 147–162. [\[CrossRef\]](#)
- Gereffi, G. (1999). International trade and industrial upgrading in the apparel commodity chain. *Journal of International Economics*, 48(1), 37–70. [\[CrossRef\]](#)
- Hannan, M. T., & Freeman, J. (1984). Structural inertia and organizational change. *American Sociological Review*, 49, 149–164. [\[CrossRef\]](#)
- Lee, K., & Malerba, F. (2017). Catch-up cycles and changes in industrial leadership: Windows of opportunity and responses of firms and countries in the evolution of sectoral systems. *Research Policy*, 46(2), 338–351. [\[CrossRef\]](#)
- Moore, J. F. (1993). Predators and prey: A new ecology of competition. *Harvard Business Review*, 71(3), 75–86. [\[PubMed\]](#)
- Nemet, G. F. (2009). Demand-pull, technology-push, and government-led incentives for non-incremental technical change. *Research Policy*, 38(5), 700–709. [\[CrossRef\]](#)
- North, D. C. (1990). *Institutions, institutional change and economic performance*. Cambridge University Press. [\[CrossRef\]](#)
- Ohtake, K. (2023). Agglomeration and welfare of the Krugman model in a continuous space. *Mathematical Social Sciences*, 123, 137–142. [\[CrossRef\]](#)
- Rajneesh, N. (2002). Innovation systems and ‘Inertia’ in R&D location: Norwegian firms and the role of systemic lock-in. *Research Policy*, 31(5), 795–816. [\[CrossRef\]](#)
- Solow, R. M. (1956). A contribution to the theory of economic growth. *Quarterly Journal of Economics*, 70(1), 65–94. [\[CrossRef\]](#)
- Tao, A. P., Li, L. X., & Hong, J. Y. (2013). Standards lock-in, heterogeneity and innovation inertia. *China Soft Science*, 201(12), 165–172.
- Teece, D. J. (1986). Profiting from technological innovation: Implications for integration, collaboration, licensing and public policy. *Research Policy*, 15(6), 285–305. [\[CrossRef\]](#)
- Xiao, X. Z., & Jiang, X. J. (2013). Allocation of government innovation funds in strategic emerging industries: Traditional transforming enterprises or new ventures? *China Industrial Economics*, (298), 128–140. [\[CrossRef\]](#)
- Zheng, S. L., & Zhang, G. G. (2022). Path analysis of manufacturing development strategy on enterprise innovation: Evidence from ten key fields. *Economic Research Journal*, 57(9), 155–173.

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