

Research Article

The Impact of Innovative Industrial Cluster Policy on Regional Innovation: Evidence from a Quasi-Natural Experiment in China

Huan Wang  and Jinhua Guo

Faculty of Business Administration, Shanxi University of Finance and Economics, Taiyuan 030006, China

Correspondence should be addressed to Huan Wang; wanghuan506@163.com

Received 26 October 2021; Accepted 22 November 2021; Published 15 December 2021

Academic Editor: Gengxin Sun

Copyright © 2021 Huan Wang and Jinhua Guo. This is an open access article distributed under the Creative Commons Attribution License, which permits unrestricted use, distribution, and reproduction in any medium, provided the original work is properly cited.

As important carriers of local innovation activities, innovative industrial clusters are attracting increasing attention. Therefore, several countries have started promotion policies for innovative industrial clusters. However, there are few empirical studies on relevant policies. This paper investigates the impact of China's "innovative industrial cluster pilot" (IICP) policy on regional innovation. Taking the implementation of IICP policy as a quasi-natural experiment and using the panel data of 266 prefecture-level cities in China in 2008-2019, this paper provides strong evidence that IICP policy promotes regional innovation. The conclusion still holds after a battery of robustness checks. The heterogeneity test shows that the promoting effect of IICP policy on innovation is more significant in central and western region than in eastern region. Moreover, the lower the city administrative level and the lower the dependence on natural resource, the more prominent the innovation effect of IICP policy. Further, the mechanism test shows that the IICP policy can promote regional innovation indirectly by strengthening government support for innovation and attracting the agglomeration of science and technological talents, but the mediation effect of industrial structure has not been verified.

1. Introduction

The role of innovation in economic growth has become widely accepted. Over the past three decades, China's innovation has experienced rapid and sustained improvement [1]. According to the Global Innovation Index (GII) 2021, which was jointly released by the World Intellectual Property Organization, Cornell University, and the European Institute of Business Administration, China's ranking has risen to 12th, becoming the only middle-income economy in the top 30 GII economies. However, compared to most developed countries, China is a latecomer in terms of developing its national innovation system and using a blend of public policies to promote innovation [2]. At present, the overall effectiveness of China's innovation system is still inadequate, and the independent innovation capacity is prominent shortcoming [3], which have become critical factors restricting the sustainable development of China's economy. Therefore, how to further stimulate

innovation becomes an important practical issue to be faced in the process of promoting the high-quality development of China's economy.

In 2012, in order to accelerate the construction of an innovative country, the State Council of China issued the "Opinions on Deepening Reform of the Science and Technology System and Accelerating the Construction of the National Innovation System", which pointed out that it is necessary to promote the aggregation of innovative elements to regional characteristic industries and promote regional innovation capability by breeding a batch of innovative industrial clusters with international competitiveness. Since then, China's central government has begun planning to implement the "innovative industrial cluster pilot" (IICP) policy. In 2013, the Ministry of Science and Technology issued the "Administration Measures for Pilot Identification of Innovative Industrial Clusters", which stated that the construction of IICPs in China started to get on track. Subsequently, a wave of striving for innovative industrial

clusters has been set off across the country. Up to now, 61 industrial clusters across the country have been selected into the pilot list of innovative industrial cluster released by the Torch Center of the Ministry of Science and Technology. With the accelerated penetration of the pilot policy, the number of IICPs continues to expand. It can be said that IICP policy is an explicit cluster policy implemented from the top down by national authorities [4]. After several years of practice, it is time to test its innovation performance. We believe that only an in-depth investigation on the effect of IICP policy can provide targeted guidance for the popularization of the policy in the future.

This paper attempts to empirically test the implementation effect of IICP policy. In China, pilot policy generally refers to the decentralization experiment carried out by the central government to seek new systems or policy instruments. Since China is a country with vast territory and enormous regional differences, the necessity for local experiments is pronounced. On the one hand, the experiments and explorations of policies by local governments can provide samples for national governance and enable the central government to gain experience from a local pilot reform pioneer [1]. On the other hand, the central government can promote such a bottom-up experiment to a national strategy and duplicate the pilot experience to more regions by a top-down strategic deployment, thus triggering the development of the whole country [5]. Previous studies have found that China's pilot policy plays an important role in promoting innovation. For example, Yao and Whalley believed that the main impacts of pilot free trade zone (PFTZ) are not on the amount of its trade volume or foreign investment, but on the promotion of institutional innovation [6]. Zheng and Li took high-tech industrial development zones (HIDZs) as the research object and confirmed that HIDZ pilot governance is conducive to the rise of innovation in China [1]. Using PSM-DID method, Ma and Li found that the pilot policy of combining technology with finance has a significant positive effect on the level of regional innovation [7]. In addition, some scholars also discussed the innovation effect of pilot policies such as carbon emissions and trading pilot [8], independent innovation demonstration zones [9], and innovation cities [10].

In summary, the established literature has examined the impact of China's pilot policies on innovation from different aspects. However, there were few studies on IICP policy and their effect. To fill this research gap, this study focuses on China's IICP policy and examines its impact on regional innovation. Treating the implementation of IICP policy as a quasi-natural experiment and using the panel data of 266 prefecture-level cities in China from 2008 to 2019, this paper attempts to answer the question of whether the IICP policy has increased the level of regional innovation. Meanwhile, in order to enrich research conclusions, this paper also examines the heterogeneity and underlying mechanism of the impact of IICP policy on regional innovation. Compared with the existing literature, this study has three main academic contributions. First, this study enriches the literatures on the assessment of pilot policy. Second, this study provides evidence on the relationship between industrial cluster and

regional innovation from the empirical perspective. Third, this paper uses city-level data, which are more reliable than the provincial data commonly used in previous studies, to conduct empirical research.

This paper is organized as follows. In Section 2, we give an overview of the IICP policy and develop our hypotheses. In Section 3, we introduce the research materials and methodology. In Section 4, we report experimental results, conduct the robustness checks, and provide further heterogeneity analysis. In Section 5, we test the influence mechanisms. In Section 6, we conclude this paper and present policy implications.

2. Policy Background and Hypothesis Development

2.1. The Background of IICP Policy. In the highly competitive industry environment, innovative clusters have received considerable attention from economists and industrial analysts. Engel and Del-Palacio defined clusters of innovation as environments that favor the creation and development of high potential entrepreneurial ventures [11]. Sun et al. believed that the increasing competition and globalization of industries, markets, and technologies have raised the demand for outside-in innovation and acquisition of technology through integrated innovation clusters [12]. Liyanage proposed that the iterative process of innovation cluster formation is an effective form of organizing a national system of innovation [13]. Debresson found that breeding innovation clusters may be the most realistic policy goal for a country in order to prime the pump of technological accumulation and bridge the technological gap with advanced industrial countries [14]. Fundeanu and Badele noted that innovative clusters were most likely to provide a new type of economy based on innovation, by means of producing dense knowledge flows for strengthening entrepreneurship by stimulating the formation of new businesses, thereby influencing the regional economic performance [15]. Yıldız and Aykanat believed that innovative clusters are inclined to make sustainable innovation in their goods and services systems and processes, as well as in their management systems and processes [16]. From the literature review, theoretical research on innovation cluster is on the rise, and most academic literature affirms the positive role of innovation clusters, while the empirical research on the effect of innovation cluster has not been addressed. The innovative industrial cluster pilot policy in China provides a chance to remedy this research gap.

Innovative industrial cluster pilots refer to industrial clusters that explore experience and form demonstration effects in independent innovation under the support and guidance of the government, including strategic emerging industrial clusters or traditional industrial clusters that are undergoing transformation. The construction of innovative industrial clusters in China is an exploratory development process from shallow to deep. By the end of 2020, the Ministry of Science and Technology announced three batches of pilot lists of innovative industrial cluster in accordance with the management measures for pilot identification. Specifically, in

2013, the first batch of IICPs was announced, and 10 clusters including Beijing Zhongguancun Mobile Internet Cluster were identified. In 2014 and 2017, the second batch of 22 pilot units and the third batch of 29 pilot units were released, respectively. Accordingly, the number of IICPs in China has increased to 61, and these pilots are distributed in 55 cities across the country.

According to statistical data from the “*China Torch Yearbook*”, the implementation of IICP policy has achieved remarkable achievements. In 2019, China’s innovative industrial clusters created operating revenue of 5739.67 billion, total industrial output value of 4506.69 billion, net profit of 419.26 billion, tax payments of 307.42 billion, and export earnings of 112.4 billion dollars. In terms of scientific and technological achievements, China’s innovative industrial clusters have obtained 35530 invention patents and 147191 registered trademarks and established 1100 national or industrial standards. In 2020, the Ministry of Science and Technology issued the “Opinions on Further Promoting the High-Quality Development of Innovation Industrial Clusters”, requiring all regions and relevant departments to implement the tasks proposed in this guideline to ensure the high-quality and orderly advancement of innovative industrial clusters. The opinion also suggested that in the coming period, China will continue to expand the scope of IICPs and strive to build a number of innovative industrial clusters with international leading positions. Therefore, it is necessary to evaluate the effect of IICP policy, so as to get replicable and popularized experience.

2.2. Hypothesis Development

2.2.1. Effect of IICP Policy on Regional Innovation. Innovative industrial clusters are the advanced stage of the development of local industrial clusters [17]. The formation of innovative industrial cluster can optimize regional innovation environment and make up for the deficiencies of regional innovation system. This is reflected in the following: Firstly, innovative industrial clusters provide good incubations and growth environment for innovative enterprises by establishing professional services support system including science and technology, management, and finance, thereby promoting the development of local innovative enterprises. Secondly, compared with traditional industrial clusters, innovative industrial clusters focus more on encouraging synergy and enabling various parties to work in a common purpose, thus helping to strengthen regional innovation system [18]. Thirdly, innovative industrial clusters are conducive to improving the modernization level of regional industries due to its important carrier for cultivating and developing knowledge or technology-intensive industries such as high-tech industries and strategic emerging industries [19]. The IICP policy is an important policy exploration to accelerate the formation and development of local innovative industrial cluster; it is expected that the implementation of IICP policy will promote regional innovation. To verify whether this impact exists, this paper proposes the first research hypothesis:

Hypothesis 1. The IICP policy has a positive impact on regional innovation.

2.2.2. The Impact Mechanism of IICP Policy on Regional Innovation. The IICP policy promotes region innovation through the following transmission mechanisms. Firstly, The IICP policy strengthens government support for innovation. In practice, innovation not only needs to be driven by the market, but also requires state participation and government guidance to make up for market failures [10]. The industrial development strategy of a region will not be endogenous with the regional economic growth but requires the government to play the role of growth identification and facilitation [20]. The implementation of IICP policy urges the government to guide the allocation of innovation resources to industries with development advantages at the strategic level, thereby improving the utilization efficiency of regional innovation elements. In addition, one of the main tasks of the pilot policy is to support technological innovation of technology-based SMEs. As we all know, technological innovation has the characteristics of strong externalities, large investments, and high risks, coupled with the current extremely unbalanced resource allocation in China’s financial market, causing a large number of SMEs to face serious financing constraints [7]. These phenomena will greatly limit local technology-based SMEs to conduct innovation. The IICP policy requires local government to increase financial support for technology-based SMEs, so as to alleviate the financial constraints of technology-based SMEs to carry out innovative activities and make up for shortcomings in the allocation of market resources, thus promoting the enhancement of regional innovation vitality.

Secondly, the IICP policy attracts the agglomeration of scientific and technological talents. As a key element of innovation, scientific and technological talents support the high-level and sustainable development of innovative industrial clusters. The IICP policy takes “cultivating talents and strengthening talent strategy” as an important goal, and includes a series of supporting policies for the introduction of innovative talents. For example, to support the pilot construction, the local government encourages enterprises and scientific research institutions in the cluster to set up various types of working platforms for high-level professional and technical talents, promotes the implementation of major talent projects such as overseas high-end technology and leading talent introduction plan, and explores the establishment of a flexible working mechanism for scientific and technological talents, etc. Driven by the pilot policy, a number of high-level scientific and technological talents flow into the local region, thus improving the supply capacity of regional talent elements. Moreover, the larger the stock of scientific and technological talents in a region, the richer its knowledge accumulation and technical reserves, which can timely meet the innovation investment needs of enterprises and promote the development of regional innovation activities [21]. Besides, the stock of scientific and technological talents determines the absorptive capability of a city. A city with more scientific and technological talents tends to have a

stronger ability to recognize, transform, and creatively apply new knowledge inside and outside the region, which is more conducive to increasing the regional innovation output [22]. In particular, in the process of gathering scientific and technological talents, knowledge will be transferred, diffused, and reorganized among talents with different technical backgrounds, thereby promoting the diversification of innovation results [23].

Finally, the IICP policy drives the optimization of industrial structure. There are obvious differences in innovation vitality between different industries [24]. Generally speaking, the innovation intention of labor-intensive industries is not strong, and the technology-intensive and knowledge-intensive industries are the main force of innovation [25]. The optimization of industrial structure is realized in the sequential evolution of labor-intensive, capital-intensive, and technology-intensive industries [26]. In the process of optimizing the industrial structure, regional innovation resources can be allocated more and more reasonably, and on this basis, the efficiency of regional technological innovation would also be improved. The implementation of IICP policy is conducive to promoting the optimization of the industrial structure. On the one hand, IICP policy aims to promote the transformation of local traditional industries from relying on “resource dividend” to relying on “innovation dividend” [19]. Under the guidance of policy, the regional elements are transferred from low-efficiency production sectors to high-efficiency production sectors, and the industrial structure is optimized accordingly. On the other hand, the IICP policy includes a series of preferential measures to stimulate innovation, such as tax incentives, financial subsidies, preferential land use policy, and credit facilities. These preferential measures reduce the R&D cost and market uncertainty faced by enterprises, enhance the enthusiasm and initiative of enterprises for independent innovation, and promote the development of emerging industries and the upgrading of industrial chain.

Taking these findings into consideration, this paper’s second research hypothesis is as follows:

Hypothesis 2. The IICP policy can promote regional innovation by strengthening government support for innovation, attracting the agglomeration of science and technological talents, and promoting the optimization of industrial structure.

3. Materials and Methods

3.1. Data. China’s Ministry of Science and Technology announced three batches of innovative industrial cluster pilot lists in 2013, 2014, and 2017, respectively. These pilot projects were distributed in 55 prefecture-level cities across the country. We regarded these 55 cities as the treated group, and other prefecture-level cities were regarded as the control group. Considering the consistency and availability of data, we removed the following unqualified city samples: (a) prefecture-level cities with administrative changes within the study period, such as Chaohu City, Bijie City, and

Tongren City; (b) prefecture-level cities with severe data loss, such as Karamay City and Wuzhong City; and (c) prefecture-level cities with innovative industrial clusters that are still in the cultivation period, but not identified as IICPs, such as Taiyuan City and Zhengzhou City. Finally, this paper selected the panel data of 266 cities in China from 2008 to 2019 as the research sample.

The data sources of this paper are as follows. Since this paper focuses on regional innovation, the invention patents were used to measure the level of regional innovation. The patent data was collected from Chinese Research Data Services Platform (CNRDS). The data on locations and buildup time of IICPs was obtained from the website of Torch High Technology Industry Development Center, Ministry of Science and Technology. The city-level data was collected from the “China City Statistical Yearbook (2009–2020)”.

3.2. Variables Explanation

3.2.1. Dependent Variable. The dependent variable of this paper is the level of regional innovation (Innov). Following Chen and Wu [27] and Zhou et al. [28], we used patent data as a measure of the regional innovation level. In China, there are three types of patents: invention patent, utility model patent, and external design patent. We believed that invention patents can be used as a more suitable indicator to measure the true level of regional innovation, because invention patents usually have higher technical content and novelty than utility model patents and external design patents. Therefore, we took the natural logarithm of the number of invention patents granted as the proxy variable for regional innovation level. It should be noted that when taking the natural logarithm, we add 1 to the number of invention patents actually granted in each region because the number of invention patents granted in some regions may be 0.

3.2.2. Independent Variable. The independent variable in this paper is IICP policy, denoted by $\text{treat} \times \text{post}$, where treat is a group dummy variable used to indicate whether the city has established innovative industrial cluster pilot. If there is at least one IICP in the city, the city belongs to the treated group, and the corresponding treat takes a value of 1. Otherwise, the city belongs to the control group, and the corresponding treat takes the value 0. post is a time dummy variable for policy implementation. For the treated group, post takes a value of 0 before the policy implementation, and post takes a value of 1 after the policy implementation. For the control group, post takes a value of 0.

3.2.3. Control Variables. To reduce the estimation bias caused by omitted variables and to effectively control the objective factors that are not considered, the following control variables were selected: (1) economic development level (Eco), measured by the natural logarithm of per-capita GDP; (2) degree of openness to the outside world (Open), measured by the proportion of foreign capital actually

utilized to GDP (foreign capital actually utilized is measured in dollars in the database, and we convert dollars into RMB by using the exchange rate); (3) financial development level (Fin), measured by the proportion of deposits and loans of financial institutions to GDP; (4) city size (Pop), measured by the natural logarithm of city's total population at the end of the year; (5) human capital level (Hum), measured by the number of college students per 10,000 people; (6) informatization level (Int), measured by the proportion of the number of Internet broadband access users to city's total population.

3.3. The Estimation Model. The time and regional variations in the adoption of the IICP policy provide an opportunity for a difference-in-differences (DID) analysis [29]. We divided the study sample into two groups, the treated group comprising cities with IICP, and the control group comprising cities without IICP. Then, we observed the effect of policy implementation by comparing the difference in city innovation level between the treated group and the control group before and after the implementation of IICP policy. The DID model in this paper is set as follows:

$$\text{Innov}_{it} = \alpha_0 + \alpha_1 \text{treat}_{it} \times \text{post}_{it} + \sum_{i=1}^N \alpha_i X_{it} + \mu_i + \vartheta_t + \varepsilon_{it}, \quad (1)$$

where i and t represent prefecture-level cities and years, respectively. Innov denotes innovation level of a prefecture-level city. $\text{treat} \times \text{post}$ is an interaction term composed of a group dummy variable and time dummy variable, and the coefficient α_1 reflects the net effect of policy implementation this paper focuses on. X_{it} represents a series of control variables changing over time at the city level. μ_i represents city fixed effects, which is used to control unobservable and time-invariant characteristics of a city. ϑ_t represents year fixed effects, which is used to control for common time trends. treat_{it} and post_{it} are not included in our model individually because these variables are absorbed by the year fixed effects and city fixed effects. ε_{it} is the error term.

4. Empirical Tests and Results

In this paper, we used statistical software Stata 15.0 (StataCorp, College Station, Tex, USA) to implement analysis.

4.1. Descriptive Statistics. Descriptive statistics were captured on the main variables of the whole sample, the treated group, and the control group. The sample size (N), mean, and standard deviation (SD) of each variable are shown in Table 1. It shows that the innovation level of the treated group is significantly higher than that of the control group (the mean of Innov is 6.2511 in the treated group and 4.0105 in the control group). This result is a preliminary indication that IICP policy can promote the level of regional innovation.

4.2. Regression Analysis. Table 2 reports the estimated results of model (1). Column A reports the result without control variables. It shows that the estimated coefficient of $\text{treat} \times \text{post}$ is 0.4534, and it is significant at the level of 1%, indicating that the IICP policy has a positive impact on the level of regional innovation. Columns B-H report the results of adding the control variables one by one. It is clear that the estimated coefficients of $\text{treat} \times \text{post}$ remain statistically positive, which further confirms the conclusion that the IICP policy promotes regional innovation. Hypothesis 1 is verified.

4.3. Robustness Checks

4.3.1. Parallel Trend Test. Before the implementation of one policy, the outcome variables of the treated group and the control group should have parallel trends, which is an important prerequisite for the DID method [30]. In order to test whether the changes in innovation level of treated group and the control group meet the parallel trend before IICP policy was implemented, this paper draws the change trend chart of innovation level in treated group and control group. It can be seen from Figure 1 that the change trend of innovation level between treated group and control group was roughly the same before 2013 (when the IICP policy was first implemented). After the implementation of IICP policy, the gap of innovation level between the two groups began to widen, indicating that the research sample in this paper basically meets the premise of parallel trends.

4.3.2. PSM-DID Test. PSM (propensity score matching) is a statistical method to deal with sample selectivity bias [10]. This method can select one or more individuals from the control group whose characteristics are similar to those of the treated group by using propensity score [30]. PSM-DID means that the samples are processed by using PSM method before performing DID analysis. We first perform logit regression on the covariates (i.e., control variables) to calculate the propensity score, then perform one-to-one nearest neighbor matching on the samples of treatment group according to the propensity score, and finally get 833 matching samples. The matching results are shown in Table 3, which shows that the absolute value of standardized bias of each control variable is less than 10% after matching, and the t -test result shows that there is no significant systematic difference between the treated group and the control group after matching, which means that the matched data meet the parallel premise. In order to see the difference between matched samples and unmatched samples more intuitively, we drew Figure 2 to show the standard deviations change of each variable before and after matching. It can be seen from Figure 2 that the standardized bias across covariates after matching is close to 0, which further verifies the validity of the matching data. Using the matched sample to conduct regress analysis, it is found that IICP policy still has a significantly positive impact on the level of regional innovation ($\beta = 0.4884$). The results are reported in column A of Table 4.

TABLE 1: Description of main variables.

Variable	Total sample			Treated group			Control group		
	<i>N</i>	Mean	SD	<i>N</i>	Mean	SD	<i>N</i>	Mean	SD
Innov	3192	4.4737	1.9281	660	6.2511	1.9846	2532	4.0105	1.6195
Eco	3192	1.3135	0.6535	660	1.7153	0.5822	2532	1.2088	0.6302
Open	3192	0.0175	0.0184	660	0.0260	0.0203	2532	0.0153	0.0172
Fin	3192	2.2546	1.1592	660	2.6048	1.2476	2532	2.1634	1.1174
Pop	3192	5.8680	0.7139	660	6.2109	0.6660	2532	5.7786	0.6989
Hum	3192	4.5179	1.0903	660	5.3232	0.9401	2532	4.3080	1.0274
Int	3192	0.3654	1.0426	660	0.2736	0.6722	2532	0.3893	1.1181

TABLE 2: Regression results for the impact of IICP policy on regional innovation.

Variable	A	B	C	D	F	G	H
treat × post	0.4534*** (4.42)	0.4737*** (4.84)	0.4755*** (4.85)	0.4785*** (4.87)	0.4784*** (4.86)	0.4787*** (4.87)	0.4399*** (4.58)
Eco		0.5163*** (4.12)	0.5112*** (4.08)	0.5372*** (4.11)	0.5372*** (4.10)	0.5403*** (4.10)	0.5530*** (4.43)
Open			0.5192 (0.46)	0.5087 (0.45)	0.5090 (0.45)	0.5089 (0.45)	0.5743 (0.53)
Fin				0.0203 (0.81)	0.0203 (0.81)	0.0214 (0.86)	0.0290 (1.11)
Hum					-0.0010 (-0.01)	-0.0029 (-0.04)	0.0632 (0.81)
Int						0.0092 (0.75)	0.0156 (1.25)
Pop							1.2071*** (3.07)
_cons	3.0044*** (85.45)	2.6389*** (28.45)	2.6312*** (27.49)	2.5777*** (21.96)	2.5821** (8.06)	2.5827*** (8.08)	-4.7684* (-1.93)
City FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R ²	0.7390	0.7447	0.7447	0.7448	0.7446	0.7449	0.7487
<i>N</i>	3192	3192	3192	3192	3192	3192	3192

Notes. *t*-statistics are in parentheses. *, **, ***Statistical significance at the 10%, 5% and 1% levels, respectively; _cons represent constant terms; *N* represents the number of samples.

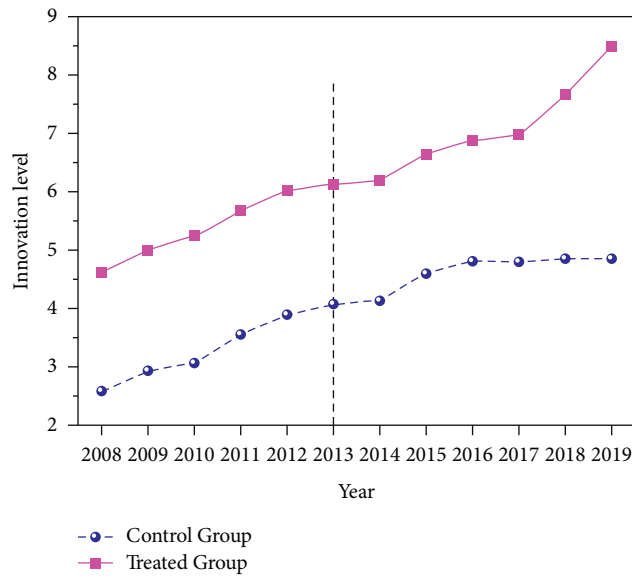


FIGURE 1: Chang trend in innovation level of the treated and control group.

TABLE 3: The result of PSM matching.

Variables	Unmatched/matched	Mean		Bias (%)	Reduct bias (%)	<i>t</i> -test	
		Treated group	Control group			<i>t</i> -statistics	<i>P</i> > <i>t</i>
Eco	U	1.7153	1.2088	83.5	96.8	18.67	0.000
	M	1.7138	1.6978	2.6		0.51	0.713
Open	U	0.0260	0.0153	57.0	92.9	13.72	0.000
	M	0.0259	0.0252	4.0		0.67	0.504
Fin	U	2.6048	2.1634	37.3	94.2	8.82	0.000
	M	2.6033	2.5776	2.2		0.39	0.695
Pop	U	6.2109	5.7786	63.3	95.7	14.29	0.000
	M	6.2099	6.2285	-2.7		-0.52	0.604
Hum	U	5.3232	4.3080	103.1	99.9	23.00	0.000
	M	5.3206	5.3197	0.1		0.02	0.985
Int	U	0.2736	0.3893	-12.5	32.5	-2.54	0.011
	M	0.2740	0.1958	8.5		2.62	0.009

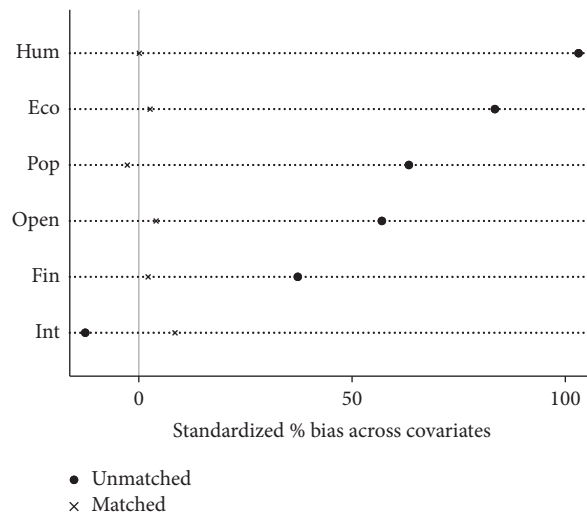


FIGURE 2: The standardized bias across covariates before and after matching.

TABLE 4: The result of robustness test.

Variable	A	B	C	D
treat × post	0.4884*** (4.48)	0.5512*** (4.83)	0.7592*** (4.80)	0.3726*** (3.95)
_cons	-4.3794 (-0.77)	-3.2738 (-1.39)	-2.7332 (-1.00)	-5.3238** (-1.99)
Controls	Yes	Yes	Yes	Yes
City FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
<i>N</i>	833	2926	2660	3192
<i>R</i> ²	0.7902	0.7090	0.6694	0.7537

Notes. *t*-statistics are in parentheses; **, *** statistical significance at the 5% and 1% levels, respectively; controls represent control variables; _cons represent constant terms; *N* represents the number of samples.

4.3.3. *Placebo Test.* In order to further test whether omitted variables may affect the conclusion of this paper, we conducted a placebo test. Specifically, we replaced the samples of the treated group randomly, and then we combined the new group dummy variable with the time dummy variable (*post*) to form a virtual interaction term for regression. Since the treated group is randomized, the fictitious interaction term should not have a significant impact on the explained

variable. That is to say, if the estimated coefficient of the fictitious interaction item is significant, this means that there is recognition error in the model setting; that is, other factors that promote the level of regional innovation are omitted. If the estimated coefficient of the fictitious interaction item is not significant, this means that there is no significant omitted variable deviation. We took the virtual interaction term into (1) to perform regression and repeated this

regression process 1000 times. Then, we draw the kernel density estimation diagram of t -statistics according to the estimation coefficient and standard error of the virtual interaction term in each regression result. As shown in Figure 3, we can see that the absolute values of most t -statistics are within 2, which proves that the deviation of the estimation results caused by the omitted variables in this paper is not obvious. The previous conclusion still holds.

4.3.4. Changing the Measurement of Dependent Variable.

In China, the authorization of invention patents usually lags 1-2 years. In order to mitigate the influence of patent grant lag on the research conclusions, this paper conducts robustness tests by replacing the dependent variable with its lagged value. As shown in Table 4, column B reports the result when the dependent variable is lagged by one period, and column C reports the result when the dependent variable is lagged by two periods. The results show that, after changing the dependent variable, the estimated coefficient on $\text{treat} \times \text{post}$ is still positive and significant, indicating that the conclusion of this paper is robust.

4.3.5. Excluding Extreme Values.

In order to mitigate the influence of outliers on the research conclusions, we winsorized all continuous variables at the level of 1% and 99% and implemented a regression analysis by using the processed samples. The results are shown in column D of Table 4. It shows that the estimated coefficient of $\text{treat} \times \text{post}$ is still significantly positive, further validating the robustness of our conclusion.

4.4. Heterogeneity Analysis.

From the above results, it is found that there is a positive correlation between IICP policy and regional innovation. Next, we will further explore whether there is heterogeneity in this positive relationship.

Firstly, we examined the heterogeneity due to geographical location. According to the geographical location of the city, we divide the sample into two subsamples: eastern cities and noneastern (central and western) cities. We also construct a geographical location dummy variable (location) and set the location value of eastern cities to 1 and that of noneastern cities to 0. Columns A–C of Table 5 report the result. The result shows that the IICP policy has a significant and positive impact on innovation of both eastern cities and noneastern cities. Further, we find that the coefficient of $\text{treat} \times \text{post} \times \text{location}$ is negative (-0.1788) and statistically significant at the level of 5%. This indicates that the IICP policy plays a more significant role in promoting innovation in noneastern regions than in the eastern region. This may be due to the imbalance regional development in China. The eastern region is considered to be the birthplace of China's modern economy due to its natural coastal advantages. After years of leading development, this region has gathered a large number of innovative resources such as advanced technology, high-quality talents, and research institutions. However, due to the weak economic and technological foundation, poor infrastructure construction, and other factors, the central and

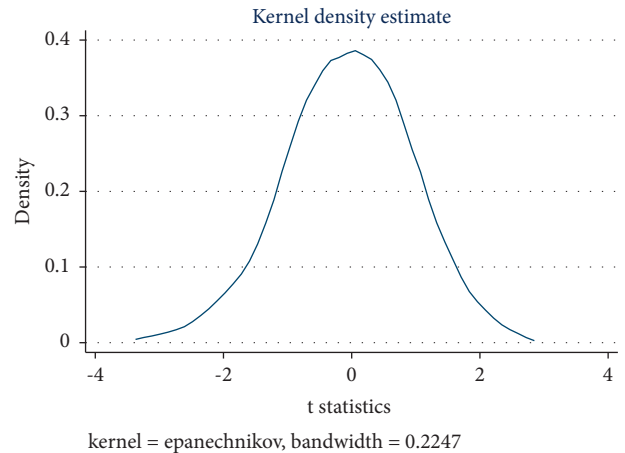


FIGURE 3: The result of the placebo test.

western regions are relatively backward in terms of innovative economy development. Therefore, the same innovation pilot policy has a greater innovation driving effect in the underdeveloped regions of the central and western regions.

Secondly, we examined the heterogeneity due to administrative level. According to the administrative hierarchy of cities in China, we define municipalities, provincial capitals, and sub-provincial cities as high-level cities, and other prefecture-level cities as low-level cities. We also construct a hierarchy dummy variable (level) and set the level value of high-level cities to 1 and that of low-level cities to 0. Columns D–F of Table 5 report the result, which shows that the IICP policy has a significant and positive impact on innovation of both low-level cities and high-level cities. Further, we find that the coefficient of $\text{treat} \times \text{post} \times \text{level}$ is negative (-0.5435) and statistically significant at the level of 1%. This indicates that the IICP policy plays a more significant role in promoting innovation in low-level cities than in high-level cities. The possible reason for this difference is that high-level cities have good economic conditions, have gathered a large number of innovation resources, and have established effective innovation ecosystems. Even without IICP policy, the innovation capability of these cities is still in a high position. That is to say, the IICP policy is just the icing on the cake for high-level cities. For low-level cities, their innovation capability lags behind those high-level cities, and the implementation of the IICP policy can tap the potential of regional innovation and drive the agglomeration of innovation resources. Therefore, the IICP policy has greater marginal effect in promoting innovation of low-level cities.

Thirdly, we examined the heterogeneity due to resource endowment. Based on the classification standard of the “Sustainable Development Plan for Resource-Based Cities” issued by the State Council in 2013, we divide the sample into two subsamples: resource-based cities and non-resource-based cities. We also construct a resource endowment dummy variable (resource) and set the resource value of resource-based cities to 1 and that of non-resource-based cities to 0. Columns G–I of Table 5 report the result. The result shows that the IICP policy has a significant and positive impact on innovation of non-resource-based cities,

TABLE 5: The result of heterogeneity test.

Variable	A Geographical location		C	D Administrative level		F	G Resource endowment		H
	East	Non-east	—	High	Low	—	Resource-based	Non-resource-based	
treat × post	0.4494*** (4.15)	0.4366*** (2.99)	0.5981*** (8.11)	0.2323* (2.05)	0.5984 *** (5.22)	0.6201*** (5.38)	0.1617 (0.74)	0.5106*** (5.02)	
treat × post × location			-0.1798 * (-1.95)						
treat × post × level						-0.6146 *** (-3.78)			
treat × post resource									
_cons	6.1721 (0.95)	-6.2203*** (-2.95)	-0.6757 (-0.56)	0.2027 (0.06)	-8.9415*** (-4.02)	-5.3100** (-2.38)	-9.4946*** (-4.11)	0.4624 (0.12)	
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	
City FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	
N	1020	2172	3192	336	2856	3192	1284	1908	
R ²	0.8192	0.7228	0.7704	0.8644	0.7486	0.7526	0.7213	0.7716	

Notes. *t*-statistics are in parentheses; *, **, *** statistical significance at the 10%, 5%, and 1% level, respectively; controls represent control variables; _cons represent constant terms; *N* represents the number of samples.

but the impact on resource-based cities is not significant. This indicates that the IICP policy plays a more significant role in promoting innovation in non-resource-based cities than in resource-based cities. This may be due to the fact that resource-based cities generally suffer from “resource curse” phenomena such as “Dutch disease” and crowding out effect. The economic development of these cities has been excessively dependent on natural resources for a long time, which makes the innovation pilot policy have no substantial promotion effect on regional innovation.

5. Mechanism Tests

In Section 2 of this paper, we propose that the IICP policy can promote regional innovation by strengthening government support for innovation, attracting the agglomeration of science and technological talents, and promoting the optimization of industrial structure. To verify the above mechanism, we draw on the mediation effect model of Baron and Kenny [31]. On the basis of Model (1), we construct the following mediation effect model:

$$M_{it} = \gamma_0 + \gamma_1 \text{treat}_{it} \times \text{post}_{it} + \sum_{i=1}^N \gamma_i X_{it} + \mu_i + \vartheta_t + \varepsilon_{it}, \quad (2)$$

$$\text{Innov}_{it} = \rho_0 + \rho_1 \text{treat}_{it} \times \text{post}_{it} + \rho_2 M_{it} + \sum_{i=1}^N \alpha_i X_{it} + \mu_i + \vartheta_t + \varepsilon_{it}, \quad (3)$$

where *M* represents intermediary variable and other regression variables are consistent with Model (1). According to Baron and Kenny, to establish a partial mediation relationship between IICP policy and regional innovation, the following conditions must be held: (a) IICP policy must have a positive effect on regional innovation in Model (1), which has been

confirmed above, (b) IICP policy should have a positive impact on intermediary variable in the first equation of Model (2), (c) the intermediary variable must have a positive effect on regional innovation in the second equation of Model (2), and (d) the effect of the IICP policy on regional innovation must be less in Model (2) than that in Model (1). Perfect mediation holds if the direct effect of the IICP policy on regional innovation is not significant in Model (2). Next, we test whether these conditions are complied with in this study.

5.1. Government Support (Govs). Drawing on the practice of Li and Xing [3], the share of local fiscal expenditure on science and technology as a percentage of general local budget expenditure is used as a measure of the strength of government support for innovation. To test the mediating role of government support for innovation between IICP policy and regional innovation, we examined and compared the regression results of Model (2). As shown in columns A and B of Table 6, we found that all the mediating conditions set by Baron and Kenny are satisfied. This suggests that government support for innovation plays a partial mediator role between IICP policy and regional innovation. Moreover, the indirect effect of IICP policy on regional innovation by strengthening government support for innovation is about 0.03 (0.0047×6.6056).

5.2. Science and Technological Talents (Tag). Based on related research [23], we define the agglomeration degree of science and technological talents as the number of scientific and technological talents per 10000 people, that is, “the proportion of science and technological talents to the total population of the city”. The calculation formula is as follows:

$$\text{Tag}_{i,t} = \frac{T_{i,t}}{E_{i,t}}, \quad (4)$$

TABLE 6: The result of mechanism test.

Variable	A Govs	B Innov	C Tag	D Innov	E IS	F Innov
treat×post Govs	0.0047*** (2.82)	0.4088*** (4.33)	0.1267*** (2.96)	0.4197** (4.42)	-0.0176*** (-2.98)	0.4438*** (4.60)
Tag				0.1598*** (3.33)		
IS						0.2162 (1.13)
_cons	-0.1652*** (-4.10)	-3.6771 (-1.48)	4.4135*** (3.55)	-5.4737* (-2.23)	2.6066*** (12.61)	-5.3319** (-2.12)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
City FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
R ²	0.1302	0.7514	0.2605	0.7510	0.6483	0.7489
N	3192	3192	3192	3192	3192	3192

Notes. *t*-statistics are in parentheses; *, **, *** statistical significance at the 10%, 5%, and 1% level, respectively; controls represent control variables; _cons represent constant terms; *N* represents the number of samples.

where *i* and *t* represent prefecture-level cities and years, respectively. T_{it} indicates the total number of science and technology personnel in a city. E_{it} indicates the total population of a city. In order to eliminate heteroscedasticity, we take the natural logarithm of this indicator for regression. Likewise, we test the mediating role of science and technological talents agglomeration between IICP policy and regional innovation by examining and comparing the regression results of Model (2). Referring to columns C and D of Table 6, we found that all the mediating conditions set by Baron and Kenny are satisfied. This suggests that the agglomeration of science and technological talents plays a partial mediator role between IICP policy and regional innovation. The indirect effect of IICP policy on regional innovation by promoting the agglomeration of technological talents is about 0.02 (0.1267×0.1598).

5.3. Industry Structure (IS). The existing indicators for evaluating industrial structure include the proportion of the output value of nonagricultural industrial in GDP [10] and the ratio of the output value of the tertiary industry to the output value of the secondary industry [26]. However, a common limitation of the above indicators is that they ignore the role of the primary industry. On the whole, the proportion of secondary and tertiary industries in China is increasing. However, in the central and western regions, the proportion of primary industry in some cities is still between 30% and 40%. Therefore, in order to fully investigate the role of the three industries in the process of structural adjustment, this paper sets the industrial structure index as shown in equation (4) with reference to the practice of Ji [25].

$$IS_{i,t} = \sum_{m=1}^3 y_{i,m,t} \times m, \quad m = 1, 2, 3, \quad (5)$$

where *i* and *t* represent prefecture-level cities and years, *m* represents the industry, and *y* represents the ratio of output value of the *M* industry to GDP. The larger the value of IS, the more advanced the industrial structure.

To test the mediating role of the industrial structure between IICP policy and region innovation, we also examined and compared the results of Model (2). The path

coefficient estimation results of Model 2 and Model 3 are shown in columns E and F of Table 6. Contrary to our expectations, IICP policy has not promoted the optimization of the industrial structure. This may be because the implementation time of IICP policy is relatively short and the number of pilots is relatively small, while the optimization of the industrial structure requires longer period [26]. Therefore, IICP policy failed to improve the regional innovation capability by promoting the optimization of industrial structure.

In summary, the hypothesis that IICP policy indirectly promotes regional innovation by strengthening government support for innovation and attracting the agglomeration of science and technological talents has been verified, but the mediation effect of industrial structure has not been verified. Thus, hypothesis 2 is partially verified.

6. Conclusions and Policy Implications

This study empirically examines the impact of innovative industrial cluster pilot policy on regional innovation. Based on the panel data of 266 prefecture-level cities in China from 2008 to 2019 and taking the establishment of innovative industrial cluster pilot as a quasi-natural experiment, this paper provides supportive evidence that there is a positive relationship between IICP policy and regional innovation. In other words, the construction of innovative industrial cluster pilot can promote regional innovation. In addition, the positive association remains stable after the parallel trend test, PSM-DID test, placebo test, changing the measurement of dependent variable, and excluding extreme values. The heterogeneity test shows that the promoting effect of IICP policy on innovation is more significant in central and western region than in eastern region. Moreover, the lower the administrative level of the city and the lower the natural resource dependence, the more prominent the innovation effect of IICP policy. Further, the mechanism analysis shows that the IICP policy can promote regional innovation indirectly by strengthening government support for innovation and attracting the agglomeration of technological talents, but the mediation effect of industrial structure has not been verified.

We present the following policy recommendations, which are based on the results of this study. First, the innovative effect of innovative industrial cluster pilot as a “policy experiment” has been proved in this paper. In order to further exert the positive externalities of this policy, China should further expand the pilot scope of innovative industrial cluster, popularize the valuable experience of implementing IICP policy in other region where it has not yet been implemented, and enhance the radiation and driving effect of innovative industries on regional innovation.

In addition, the implementation of IICP policy should adhere to the principle of adjusting measures to local conditions and avoid blind following and simplified imitating. According to the heterogeneity of policy effect, it is necessary to give priority to establishing pilot projects in China's central and western regions, and cities with lower administrative levels or lower dependence on resources, and then gradually extend the pilot projects across the country. Meanwhile, the regions in which IICPs are located should strive to explore the diversified experience of pilot construction, discover general rules, and contribute material to the central government's policy formulation. Only by accelerating the formation of an interactive mechanism in which the central government provides innovative strategic guidance and institutional incentives to the local government, and the local government contributes innovative practical experience and suggestions to the central government, will the IICP policy have a stronger incentive effect on regional innovation.

Finally, the total effect of the IICP policy on regional innovation is also closely related to government support and human capital level. Therefore, in order to maximize the effect of the policy, local governments should give full play to their strategic guiding function in regional innovation activities and increase fiscal expenditures on technological innovation. In addition, local governments should also formulate more attractive talent introduction policies and talent retention policies to improve local human capital supply capabilities, thus accelerating the construction of regional innovation system on this basis.

Data Availability

The data that support the findings of this study are openly available from Chinese Research Data Services Platform (<https://www.cnrds.com/>); Torch High Technology Industry Development Center, Ministry of Science & Technology (<http://www.chinatorch.gov.cn/>); and China City Statistical Yearbook (<https://data.cnki.net/Yearbook/>).

Conflicts of Interest

The authors declare that there are no conflicts of interest regarding the publication of this paper.

References

- [1] S. L. Zheng and Z. C. Li, “Pilot governance and the rise of China's innovation,” *China Economic Review*, vol. 63, Article ID 101521, 2020.
- [2] F.-C. Liu, D. F. Simon, Y.-T. Sun, and C. Cao, “China's innovation policies: evolution, institutional structure, and trajectory,” *Research Policy*, vol. 40, no. 7, pp. 917–931, 2011.
- [3] J. Li and J. Xing, “Why is collaborative agglomeration of innovation so important for improving regional innovation capabilities? A perspective based on collaborative agglomeration of industry-university-research institution,” *Complexity*, vol. 2020, Article ID 7049606, 21 pages, 2020.
- [4] M. Fromhold-Eisebith and G. Eisebith, “How to institutionalize innovative clusters? Comparing explicit top-down and implicit bottom-up approaches,” *Research Policy*, vol. 34, no. 8, pp. 1250–1268, 2005.
- [5] S. Heilmann, “From local experiments to national policy: the origins of China's distinctive policy process,” *The China Journal*, vol. 59, pp. 1–30, 2008.
- [6] D. Yao and J. Whalley, “The China (Shanghai) pilot free trade zone: background, developments and preliminary assessment of initial impacts,” *The World Economy*, vol. 39, no. 1, pp. 2–15, 2016.
- [7] L. Y. Ma and X. M. Li, “Does science and technology finance policies promote regional innovation? Quasi-natural experiment based on the pilot policy of combining science and technology with finance,” *China Soft Science*, vol. 33, no. 12, pp. 30–42, 2019.
- [8] W. Liu, C. Yu, S. Cheng, J. Xu, and Y. Wu, “China's carbon emissions and trading pilot, political connection, and innovation input of publicly listed private firms,” *International Journal of Environmental Research and Public Health*, vol. 17, no. 17, p. 6084, 2020.
- [9] J. H. Guo, M. N. Guo, S. F. Guo, and S. S. Zhang, “Dose the innovation policy pilot promotes enterprise innovation effectively in China? Empirical evidence from the construction of national independent innovation demonstration zones,” *Industrial Economics Research*, vol. 2, pp. 56–70, 2021.
- [10] Z. Li and S. Y. Yang, “Has the pilot project of innovation City increased the level of urban innovation?” *Economic Perspectives*, vol. 8, pp. 70–85, 2019.
- [11] J. S. Engel and I. Del-Palacio, “Global networks of clusters of innovation: accelerating the innovation process,” *Business Horizons*, vol. 52, no. 5, pp. 493–503, 2009.
- [12] C.-C. Sun, G. T. R. Lin, and G.-H. Tzeng, “The evaluation of cluster policy by fuzzy MCDM: empirical evidence from HsinChu Science Park,” *Expert Systems with Applications*, vol. 36, no. 9, pp. 11895–11906, 2009.
- [13] S. Liyanage, “Breeding innovation clusters through collaborative research networks,” *Technovation*, vol. 15, no. 9, pp. 553–567, 1995.
- [14] C. Debresson, “Breeding innovation clusters: a source of dynamic development,” *World Development*, vol. 17, no. 1, pp. 1–16, 1989.
- [15] D. D. Fundeanu and C. S. Badele, “The impact of regional innovative clusters on competitiveness,” *Procedia-Social and Behavioral Sciences*, vol. 124, pp. 405–414, 2014.
- [16] T. Yıldız and Z. Aykanat, “Clustering and innovation concepts and innovative clusters: an Application on Technoparks in Turkey,” *Procedia-Social and Behavioral Sciences*, vol. 195, pp. 1196–1205, 2015.
- [17] X. M. Xie, Y. H. Wu, and G. X. Ma, “Driving forces of industrial clusters towards innovative clusters: accelerating the innovation process,” *Asian Journal of Technology Innovation*, vol. 24, no. 2, pp. 161–178, 2016.
- [18] S. Herliana, “Regional innovation cluster for small and medium enterprises (SME): a triple helix concept,” *Procedia - Social and Behavioral Sciences*, vol. 169, pp. 151–160, 2015.

- [19] J. H. Li, "Distribution and cultivation strategies of innovative industrial clusters in China," *Reform*, vol. 3, pp. 98–110, 2020.
- [20] J. Lin and C. Monga, "Growth identification and facilitation: the role of the state in the dynamics of structural change," *Development Policy Review*, The World Bank, vol. 29, no. 3, pp. 259–310, 2011.
- [21] Y. Zhou, Y. Guo, and Y. Liu, "High-level talent flow and its influence on regional unbalanced development in China," *Applied Geography*, vol. 91, no. 2, pp. 89–98, 2018.
- [22] Y. Liu, J. Y. Zeng, R. Y. Wang, P. Y. Zhan, and Z. L. Pan, "The Relationship between geographical concentration of researchers and regional innovation in China," *Economic Geography*, vol. 39, no. 7, pp. 139–147, 2019.
- [23] H. J. Sun, L. N. Zhang, and S. G. Wang, "Agglomeration of scientific and technological talents, spatial spillover and regional technological innovation: a partial differential method based on spatial Dubin model," *Science of Science and Management of Science and Technology*, vol. 40, no. 12, pp. 60–71, 2019.
- [24] K. Pavitt, "Sectoral patterns of technical change: towards a taxonomy and a theory," *Research Policy*, vol. 13, no. 6, pp. 343–373, 1984.
- [25] X. Y. Ji, "Does financial geography affect urban innovation capability?" *Industrial Economics Research*, vol. 1, pp. 114–127, 2020.
- [26] C. H. Gan, R. G. Zheng, and D. F. Yu, "An empirical study on the effects of industrial structure on economic growth and fluctuations in China," *China Industrial Economics*, vol. 5, pp. 4–16, 2011.
- [27] W. Chen and Y. Wu, "China's new environmental protection law and green innovation: evidence from prefecture-level cities," *Complexity*, vol. 2021, Article ID 5566357, 13 pages, 2021.
- [28] R. Zhou, Y. Zhang, and X. Gao, "The spatial interaction effect of environmental regulation on urban innovation capacity: empirical evidence from China," *International Journal of Environmental Research and Public Health*, vol. 18, no. 9, p. 4470, 2021.
- [29] X. Cai, Y. Lu, M. Wu, and L. Yu, "Does environmental regulation drive away inbound foreign direct investment? Evidence from a quasi-natural experiment in China," *Journal of Development Economics*, vol. 123, pp. 73–85, 2016.
- [30] J. J. Heckman, H. Ichimura, and P. Todd, "Matching as an econometric evaluation estimator," *The Review of Economic Studies*, vol. 65, no. 2, pp. 261–294, 1998.
- [31] R. M. Baron and D. A. Kenny, "The moderator-mediator variable distinction in social psychological research: conceptual, strategic, and statistical considerations," *Journal of Personality and Social Psychology*, vol. 51, no. 6, pp. 1173–1182, 1986.