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Pilot Cities for Innovation and Clusters of High-Tech Talent

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Abstract

The pilot policy for national innovative cities is a key institutional arrangement in China's efforts to promote the innovation-driven development strategy and accelerate the construction of an innovative country. This paper regards this pilot policy as a quasi-natural experiment and, based on the panel data of 29 major Chinese cities from 2002 to 2019, uses a multi-period differ-ence-in-differences (DID) model to systematically assess the causal effect of the pilot policy on the spatial agglomeration of high-tech talents. The empirical re-sults show that the policy has significantly enhanced the agglomeration level of high-tech talents in the pilot cities. The heterogeneity analysis further reveals that there are obvious regional differences in the policy effects: the agglomera-tion of high-tech talents in cities of the eastern, central, and western regions has all been promoted, with the eastern region benefiting the most, followed by the western region, and the central region being relatively weaker. This reflects that the policy effects are closely related to the regional economic development level and innovation foundation. The national innovative city policy, by providing a series of support measures, offers more R&D opportunities and better innova-tion conditions for high-tech talents, thereby attracting such talents to agglom-erate in the pilot cities.

Keywords

National innovative city; High-tech talents; Talent aggregation; Location quotient

1. Introduction

Innovation is the core engine driving a country's development and progress. China has set the goal of building an innovative country as an important strategic objective. The promotion of the national pilot policy for innovative cities has a profound impact on the improvement of urban scientific and technological innovation capabilities. Scientific and technological innovation highly depends on talents as the active carrier to achieve value transformation. High-tech talents usually possess profound knowledge accumulation and technical capabilities, and demonstrate a strong willingness to explore and innovate. From the existing research, most scholars focus on the formation mechanism of high-tech industrial agglomeration or the effect of innovative city policies on the overall national innovation capacity, while dedicated studies on the impact of such policies on the agglomeration of high-tech talents are still relatively scarce. To fill this research gap, this paper constructs a measurement index system for the location entropy of high-tech talents, calculates and classifies 29 sample cities from 2002 to 2019, thereby identifying the relative levels of each city in terms of high-tech talent agglomeration. In the robustness test, this paper also controls the influence of competitive policies such as the national pilot policy for entrepreneurial cities in 2010 and the smart city pilot policy in 2012 to enhance the reliability of the estimation results. Through literature review, this paper clearly defines the core concepts of high-tech talents, talent agglomeration, and innovative cities. On this basis, by using long-term panel data, it empirically examines the promoting effect of the national pilot policy for innovative cities on the agglomeration of high-tech talents.

2. Literature Review

Innovation is the core engine driving China's economic transformation and high-quality development. Regarding the connotation of innovative cities, Ye Fan (2006) incorporated policy environment and talent resources into the evaluation system of innovative cities, emphasizing their role in shaping urban innovation capacity. As an important measure to promote the strategy of innovation-driven development, since 2008, China has promoted the construction of national innovative cities through a "pilot first, gradual promotion" approach, with Shenzhen becoming the first pilot city, marking a critical step in exploring the path of innovative cities in China. According to the "National Medium- and Long-Term Talent Development Plan Outline (2010-2020)," talent is defined as workers who possess professional knowledge or skills, are capable of carrying out creative work, and contribute to social progress, regarded as strategic resources for national development. The high-tech talent concentration discussed in this paper is an extension of the concept of talent in terms of level and scope. Wang Hongjun (2011) proposed that high-tech talent, in addition to having an innovative spirit, should also be able to apply knowledge to high-tech practices and achieve professionally recognized accomplishments. Based on this, this paper defines high-tech talent as mid- to senior-level professionals engaged in theoretical exploration or technological research and development in high-tech fields, including scientists and engineers, with relevant data mainly sourced from the "China Statistical Yearbook for Science and Technology."

With the advancement of the national innovative city pilot policies, high-tech talent has shown a trend of spatial concentration, forming a phenomenon of talent agglomeration. Zhu Xingzhen proposed that talent agglomeration is a special form of talent flow, referring to the clustering effect formed when similar or related talent gather in a certain region or industry based on specific connections over a certain period. Based on existing research, this paper defines talent agglomeration as the process in which different types of talent move toward a particular geographical space within a specific timeframe under the influence of various factors. This process not only enhances the knowledge reserves and skill levels within the region but also strengthens the overall innovation capacity of the area.

3. Design of the Location Quotient Index System for High-Tech Talent

Location Quotient (LQ) was first proposed by economist Haggett. In terms of calculation, the location quotient compares the proportion of output of a certain industry in a given region to the total output of that region with the proportion of output of the same industry at the national level to the total national output, resulting in a corresponding ratio. If the calculated result is greater than 1, it indicates that the industry has an advantage in the region above the national average; conversely, it suggests a relatively lower degree of specialization. Based on the national and selected provincial and municipal statistical yearbooks from 2002 to 2019, this paper uses the location quotient of high-tech talent as an indicator to measure the concentration of high-tech talent. Therefore, this paper defines the location quotient of high-tech talent as the ratio of the number of R&D personnel in high-tech industries in a region to the total employment in that region, compared to the number of R&D personnel in high-tech industries at the national level to the total national employment. The calculation formula is:

$$LQ_{it} = \frac{T_{xi}/T_i}{T_{xj}/T_j} \tag{1}$$

Here, LQ_{it} represents the location quotient of high-tech talent, T_{xi} is the number of high-tech industry talents in region i, T_i is the total employment in region i, T_{xj} is the number of high-tech industry talents nationwide, and T_j is the total employment nationwide.

Table 1 shows the calculated location quotient of high-tech talent averages for 29 cities in mainland China.

Table 1. Ranking Table of Location Quotients for High-Tech Talent in 29 Cities in Mainland China

Ranking	city	Location Quotient of High-Tech Talent	Ranking	city	Location Quotient of High-Tech Talent
1	Guangzhou	4.0433106	16	Anshun*	0.4032541
2	Beijing	3.952822	17	Shizuishan*	0.3554657
3	Shanghai	3.804182	18	Changsha	0.3509967
4	Hangzhou	2.1665497	19	Baoding*	0.32436497
5	Tianjin	2.0746964	20	Hefei	0.3012451
6	Suzhou	2.06415202	21	Kaifeng*	0.286174
7	Xi'an	1.7819286	22	Jilin*	0.27184654
8	Fuzhou	1.29525851	23	Haikou	0.1752692

9	Dalian	0.7537810	24	Jinchang*	0.1671362
10	Qingdao	0.6768362	25	Datong*	0.13698964
11	Wuhan	0.6700633	26	Kunming	0.09945895
12	Qiqihar*	0.66179848	27	Nanning	0.0697017
13	Mianyang*	0.63384166	28	Xining	0.05104453
14	Xinyu*	0.6014666	29	Baotou	0.0505471
15	Chongqing	0.5751997			

*. Non-national innovative city

The location quotient of high-tech talents in 29 provinces, municipalities, and autonomous regions is divided into 4 levels, as shown in Table 2:

Table 2. Level Classification

High-Tech Talent Aggregation Level	LQ value
Region of Absolute Advantage	LQ>2
Comparative Advantage Zone	2>LQ>1
comparative disadvantage area	1>LQ>0.5
Zone of Absolute Disadvantage	LQ<0.5

According to Table 2, when the location quotient is greater than 1, the region is considered to have an advantage in talent aggregation. The data show that only eight cities meet this condition, reflecting that the overall concentration of high-tech industry talent in our country is still at a relatively low level and needs to be further strengthened. Among the top ten ranked cities, Xi'an's location quotient is higher than that of most provinces and cities. One reason is that Xi'an has a dense concentration of higher education institutions and research organizations, which not only provide a substantial talent pool but also create a good environment for talent development and scientific research innovation. In contrast, the three northeastern old industrial provinces—Heilongjiang, Jilin, and Liaoning—rank 12th, 22nd, and 9th respectively, placing them at a medium level overall, reflecting that traditional industrial regions still face pressure in attracting high-tech talent. Overall, the concentration of high-tech talent in our country shows an 'east strong, west weak' gradient difference, and the central and western regions, especially the central provinces, still have considerable room for improvement in terms of talent aggregation.

4. An Empirical Study on the Concentration of High-Tech Talent in China

4.1. Model Setup

This paper focuses on an empirical study of the impact of the national pilot city policy for innovation on the agglomeration of high-tech talent. The core research idea is to compare the changes in the level of high-tech talent agglomeration in sample cities before and after the policy implementation to identify the actual effects of the policy. However, simply comparing the differences before and after the policy may be influenced by other external factors, which could lead to biased estimation results. To more accurately identify the net effect of the policy, this paper employs the difference-in-differences method for policy evaluation. This method constructs an experimental group and a control group to effectively control for time trends and individual fixed effects. Since the national pilot city policy for innovation is implemented progressively in batches, it can be regarded as a quasi-natural experiment, providing a solid practical basis for constructing a multi-period difference-in-differences model. Accordingly, this paper establishes the following model:

$$LQ_{it} = \beta_0 + \beta_1 treated * policy_{i,t} + \beta_2 controls_{i,t} + city_i + year_t + \varepsilon_{i,t} \quad (2)$$

Here, i represents the city, t represents the year, and LQ_{it} is the dependent variable, representing the location quotient index of high-tech talent in city i in year t . $treated * policy_{i,t}$ is the intervention variable; if city i in year t is designated as an innovative pilot city, then $treated * policy_{i,t} = 1$ is assigned for that year and all subsequent years after being set as an innovative pilot city, otherwise $treated * policy_{i,t} = 0$. $control_{i,t}$ represents city-related control variables. $city_i$ represents city fixed effects, controls for individual city factors; $year_t$ represents year fixed effects, controls for city-year factors. $\varepsilon_{i,t}$ denotes the unobservable random error term.

4.2. Data Source Description

After deleting samples with severe missing key data, this study ultimately identified 19 pilot cities listed in the approved national innovative pilot cities list as the intervention group, and selected 10 cities not included in the pilot list as the control group for comparative analysis. Regarding variable settings, the level of high-tech talent agglomeration is the dependent variable and is measured using the location quotient method. Data related to high-tech talent mainly come from the China High-Tech Industry Statistical Yearbook, China Statistical Yearbook, and provincial statistical yearbooks; data for control variables come from the statistical yearbooks of various provinces and relevant city statistical bulletins.

Table 3. Variables and Definitions

Variable symbol	Variable Name	Calculation method
LQ_{it}	Location Quotient of High-Tech Talent	The ratio of the proportion of R&D personnel in high-tech industries in a certain region to the total employment in that region to the proportion of R&D personnel in high-tech industries nationwide to the total national employment
$treated * policy_{i,t}$	Policy variable	In year t, the city was designated as an innovative pilot city, set to 1 for that year and thereafter, otherwise set to 0
$PerGDP$	Level of economic	Gross Domestic Product per capita

Variable symbol	Variable Name	Calculation method
	development	
Pop	Urban population density	The proportion of the total urban population to the total urban area
Edu	Level of Human Capital Development	Proportion of university students in the total population

4.3. Descriptive Statistical Analysis of Variables

The cities are divided into innovative pilot cities and non-innovative pilot cities, and descriptive statistical analysis is conducted for each. See Table 4 below.

Table 4. Descriptive Statistical Analysis of Variables

	Innovative Pilot City				Non-innovative pilot city			
Variable	Mean	Standard deviation	Maximum value	Minimum value	Mean	Standard deviation	Maximum value	Minimum value
LQ_{it}	1.191776	1.295359	6.990223	0.0354	0.384	0.287	1.711	0.038
PerGDP	45774.27	34701.61	165681	5472	24204.59	13616.6	56388	3257
Pop	669.2237	443.3492	2301.43	75.38	297.904	216.715	885.62	47.19
Edu	0.0669042	0.0465795	0.2734956	0.0004642	0.016	0.018	0.223	0
Sample size	342	342	342	342	180	180	180	180

From the table above, it can be seen that the average location quotient of high-tech talents in pilot innovative cities is 1.192, significantly higher than the 0.384 in non-pilot cities, reflecting that pilot cities generally have an advantage in attracting and concentrating high-tech talents. In terms of the distribution of extreme values, the location quotient in pilot cities fluctuates more widely, while the maximum and minimum values in non-pilot cities are 1.711 and 0.038, respectively, indicating that there are also significant differences within each type of city. Regarding control variables, the mean values of indicators such as economic development level, urban population density, and human capital development level are generally higher in pilot cities than in non-pilot cities, preliminarily suggesting that the pilot policy for innovative cities is often implemented in regions with better basic conditions, or that the policy itself has a positive effect on the overall development of cities.

4.4. Analysis of the Policy's Effect on the Concentration of High-Tech Talent

This article empirically examines the impact of innovative pilot city policies on the agglomeration of high-tech talent. First, Model 1 is estimated, and the results are shown in Table 5. In the table below, Columns (1) and (3) do not include control variables, while Columns (2) and (4) include control variables.

Table 5. Double difference results

Variable	(1)	(2)	(3)	(4)

Variable	(1)	(2)	(3)	(4)
LQ_{it}	0.9220827*** (0.1056632)	−0.4516531*** (0.0813296)	0.794897*** (0.1716767)	0.4244938*** (0.1120208)
Control variable	No	Yes	No	Yes
Urban Effect	No	No	Yes	Yes
Year effect	No	No	Yes	Yes
Sample	522	522	522	522
F-value	76.15	308.62	3.09	10.14
R^2	0.1277	0.7048	0.1580	0.6068

***, **, * indicate significance at the 1%, 5%, and 10% levels, respectively, with the numbers in parentheses representing standard errors, the same below

From Table 5, it can be seen that Column (1) shows that without adding control variables, the estimated coefficient of the innovative pilot city policy is significantly positive at the 1% level, indicating that the policy may have an initial promoting effect on the agglomeration of high-tech talents. In Column (2), after adding control variables and without using a two-way fixed effects model, the policy coefficient turns significantly negative. This result may reflect that some cities, during their expansion process, paid excessive attention to population growth while neglecting the improvement of human capital quality and investment in education. It is worth noting that when a more rigorous two-way fixed effects model is used, the regression results in Columns (3) and (4) both show that, regardless of the inclusion of control variables, the policy coefficient is significantly positive at the 1% level. This robustness check result indicates that the national innovative city pilot policy does indeed have a stable positive incentive effect on the agglomeration of high-tech talents, demonstrating that the policy has a positive effect on optimizing the allocation of talent.

4.5. Parallel Trends Test

The parallel trends test is a prerequisite for the difference-in-differences method. Before the implementation of the policy, the treatment group and the control group should have similar development trends. After the policy is implemented, the treatment group deviates from the original development trend due to the impact of the policy, while the control group continues to maintain the original trend. Therefore, following the research approach of Wang Ying and Zhou Jianjun (2021), the parallel trends test model is as follows:

$$\begin{aligned} LQ_{it} = \beta_0 &+ \beta_1 treated * policy_{i,t-3} + \beta_2 treated * policy_{i,t-2} \\ &+ \beta_3 treated * policy_{i,t-1} + \beta_4 treated * policy_{i,t} \\ &+ \beta_5 treated * policy_{i,t+1} + \beta_6 treated * policy_{i,t+2} \\ &+ \beta_7 treated * policy_{i,t+3} + \beta_8 treated * policy_{i,t+4} \\ &+ \beta_9 controls_{i,t} + city_i + year_t + \varepsilon_{i,t} \end{aligned} \tag{3}$$

In Equation (3) above, $treated * policy_{i,t}$ is used as a dummy variable for policy effects, t represents the baseline year of the experiment, that is, the year when the city became a pilot, $t-1$ is one year before the pilot, and $t+1$ is one year after the pilot. The selected time range for testing is from $t-3$ to $t+4$. To avoid collinearity issues, the year prior to the baseline is removed, and data visualization analysis is conducted using Stata 15 software. The results of the parallel trend test for the 29 cities during the three years before and four years after the pilot are shown in Figure 1. Before year t, the confidence intervals fluctuate around 0, satisfying the condition for parallel trends. After the pilot, the parallel trend is not maintained, and the effect of the pilot on talent agglomeration begins to appear that year, showing an upward trend.

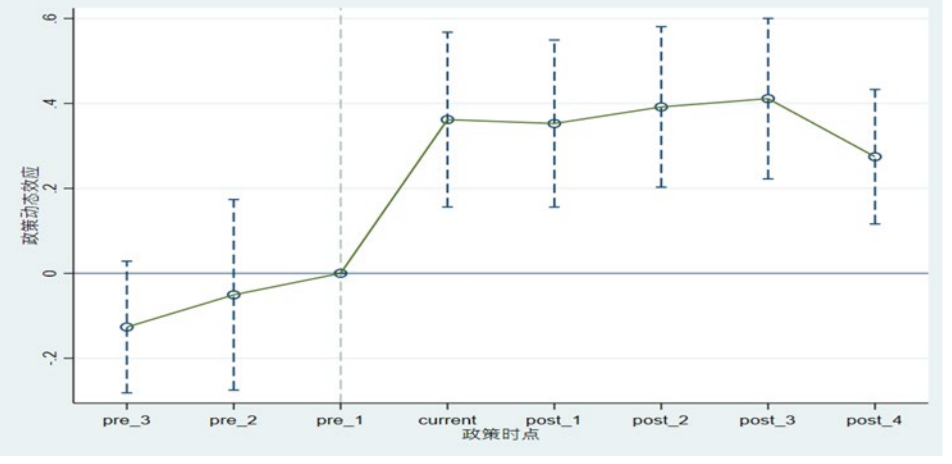

Figure 1. Parallel trend test

4.6. Placebo test

To ensure that the benchmark regression results are not affected by potential omitted variables or random factors, this study follows the research approach of Zhang Hua and Feng Chao (2021) and uses a placebo test method under a counterfactual framework to verify the robustness of the estimation results. We randomly generated 'pseudo-policy dummy variables' in the sample and conducted 1000 simulation experiments. In each experiment, the policy pilot cities were randomly reassigned, and the model was estimated based on the simulated sample. Then, the coefficients, t-values, and p-values from all simulation experiments were visualized, including plotting the coefficient kernel density, t-value distribution, and p-value scatter plot. If the coefficients of the 'pseudo-policy variables' are not statistically significant in the majority of random samples, it indicates that the policy effect observed in the original regression is not driven by random factors, thereby supporting the reliability of the benchmark results.

The test results are shown in Figures 2 and 3. In Figure 2, the red curve represents the kernel density distribution of the coefficients obtained from the 1000 placebo tests, with the peak concentrated near zero and a shape close to a normal distribution, indicating that the 'policy effect' in most random experiments is close to null. Figure 3 presents the distribution of p-values from each simulation in the form of a scatter plot, where the vast majority of points lie above the red reference line at p=0.1, indicating that these randomly generated 'policies' are not significant at the 10% significance level. Combining the results of both figures, the placebo test supports the robustness of the main conclusions of this study, and the policy effects captured in the benchmark regression are highly credible.

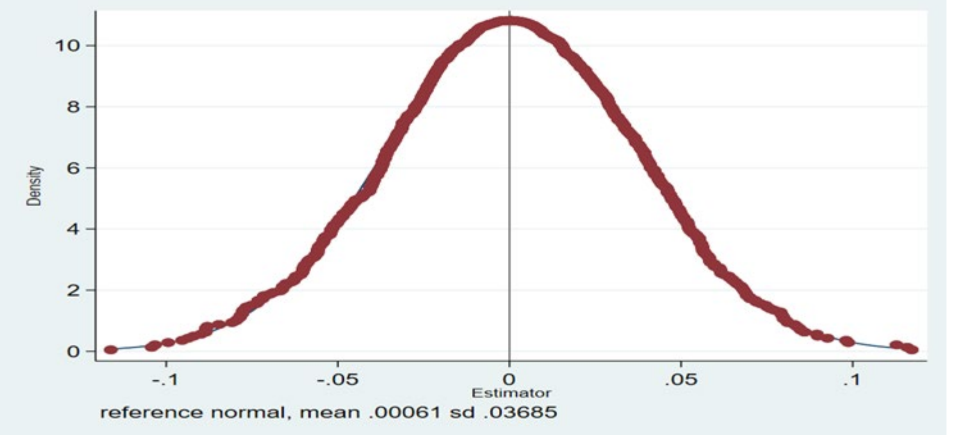

Figure 2. Kernel Density Estimate Plot

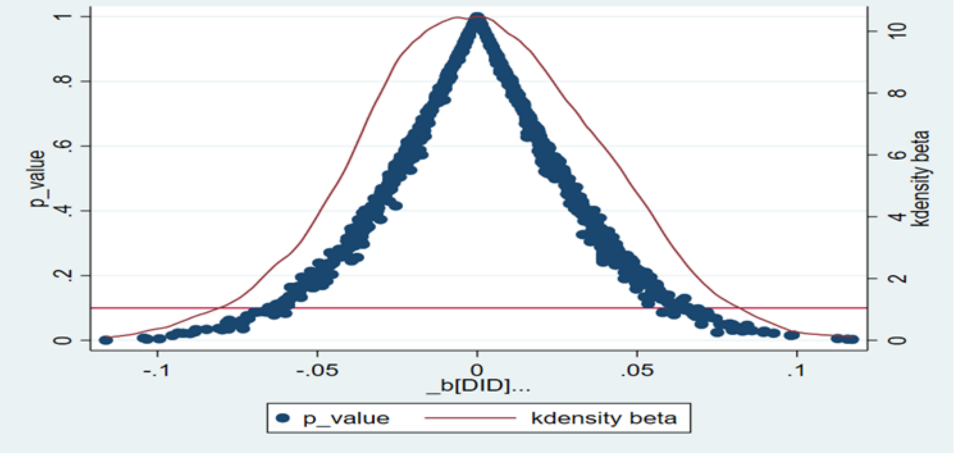

Figure 3. Placebo test

4.7. Robustness Analysis

1. Changing the Policy Implementation Time

To test the robustness of the policy effect, this study adjusts the policy implementation time from 2008 to 2010 and re-estimates the impact of the pilot policy on the agglomeration of high-tech talent. The results in Table 6 show that even after adjusting the policy timing, the coefficient for innovative city pilots remains significantly positive at the 1% level, indicating that the policy effect is temporally robust.

2. Excluding the Influence of Other Policies

To rule out potential interference from other related policies implemented at the same time, this study further controls for the entrepreneurship city pilot policy implemented from 2010 and the smart city pilot policy promoted in three batches after 2012. After introducing dummy variables for these two types of policies into the baseline regression model, Table 6 shows that the coefficient for the innovative city pilot policy remains significantly positive at the 1% level. This result indicates that even when considering the influence of entrepreneurship and smart city policies, the innovative city pilot still has an independent promoting effect on the agglomeration of high-tech talent, further supporting the reliability of the research conclusions..

Table 6. Robustness Test

Variable	(1) Change policy time	(2) Excluding the impact of other policies 1	(3) Excluding the impact of other policies 2
$treated * policy$	0.4244938*** (0.1120208)	0.5138782*** (0.128262)	0.4259149*** (0.1142477)
Ven_policy		−0.1912111 (0.1751103)	
$Smart\_policy$			0.0128164 (0.1452831)
control variable	Yes	Yes	Yes
Urban Effect	Yes	Yes	Yes
Year effect	Yes	Yes	Yes
Sample	522	522	522
R^2	0.6068	0.6168	0.6064

4.8. Heterogeneity Analysis

The city is divided into three regions—east, west, and central—for heterogeneity analysis. The difference-in-differences regression results for each region are shown in Table 7.

Table 7. Heterogeneity Test

Variable	(1) Eastern region	(2) Central Region	(3) Western Region
$treated * policy_{i,t}$	0.5942076** (0.2152053)	0.215145* (0.1042486)	0.4640886*** (0.1109215)
Urban Effect	Yes	Yes	Yes
Year effect	Yes	Yes	Yes
control variable	Yes	Yes	Yes
Sample	198	180	144
R^2	0.4278	0.0878	0.4676

As can be seen from the results in Table 7, the policy of innovative pilot cities has a promoting effect on cities in the eastern, central, and western regions, and the impact varies across different regions. The estimated coefficients of the policy effect for cities in the eastern and western regions are higher than those for the central region, with the strongest promoting effect in the eastern region. This may be because most cities in the eastern region are located along the coast, giving them advantages in terms of geographic location and natural resources, while the northeastern region has many heavy industries, abundant resources, and a relatively strong industrial and economic foundation. On the other hand, the policy has a relatively weaker impact on innovation in the central region, so it is necessary to fully stimulate the innovation potential of pilot cities in the central region, and the government should increase investment in innovation.

5. Conclusion and Outlook

High-tech talent serves as a core element in driving a nation toward high-quality development, making its cultivation and attraction strategically important. Innovation is the fundamental driver of high-quality economic development. To strengthen innovation leadership and seize the strategic high ground of future development, building innovative cities must be treated as a key approach. Through institutional innovation and policy coordination, the national innovation system can be continuously optimized. As a policy practice with exploratory significance, the pilot program for national innovative cities plays an irreplaceable role in guiding the spatial concentration of high-tech talent. Based on panel data from 29 Chinese cities from 2002 to 2019, this study treats the pilot policy for national innovative cities as a quasi-natural experiment, constructing a multi-period difference-in-differences (DID) model to systematically evaluate the policy's impact on the aggregation of high-tech talent, and further conducts an analysis of regional heterogeneity. The results indicate that the pilot policy for national innovative cities significantly enhances the aggregation of high-tech talent in the pilot areas. In terms of regional differences, the policy promotes talent concentration in the eastern, central, and western regions, but with varying intensity: the effect is strongest in the eastern cities, followed by the western cities, and relatively weaker in the central region.

It should be noted that this study still has certain limitations and areas for improvement. First, the limited number of selected city samples may affect the generalizability of the conclusions, and future research could expand the sample range to enhance representativeness. Second, the data mainly come from publicly available statistics, which may involve systematic biases during collection and publication, requiring cautious interpretation of results. Finally, as China’s urbanization accelerates and the innovation strategy deepens, the pattern of urban development and mechanisms of talent mobility will dynamically evolve, so subsequent research needs to continuously track policy developments and real-world changes to increase timeliness and explanatory power. At the policy level, the pilot program for national innovative cities provides systematic support for enterprises to enhance innovation performance through multiple pathways, including creating an innovation-friendly institutional environment, increasing investment in R&D resources, improving talent incentive mechanisms, and strengthening industry-academia-research collaboration. These measures collectively optimize the regional innovation ecosystem, offering high-tech talent broader development platforms and superior innovation conditions, thereby effectively promoting their concentration in pilot cities and forming a positive cycle of mutual promotion between talent and innovation.

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