

How Local Talent Introduction Policies Influence Enterprise Innovation

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Abstract: Talent is the driving force behind enterprise innovation. Taking talent introduction policies as a quasi-natural experiment, this study draws on data from local talent introduction policies issued between 2016 and 2019. By leveraging the variations in the timing of policy implementation across different cities, we employ a Difference-in-Differences (DID) model to empirically examine the mediating role of enterprise labor resource allocation in the relationship between talent policies and enterprise innovation. The findings indicate that local talent introduction policies significantly promote enterprise innovation. Mechanism analysis confirms that labor resource allocation acts as a mediating channel. Specifically, the implementation of these policies optimizes the labor structure within firms, enhances the overall quality and innovative capabilities of the workforce, and thereby drives improvements in firms' innovation performance. These conclusions offer valuable policy insights for local governments aiming to refine talent incentive programs and implement innovation-driven development strategies. Enhancing the precision and effectiveness of talent policies through the optimization of talent resource allocation can ultimately strengthen enterprises' innovative capacities.

Keywords: Local talent introduction policy, enterprise innovation, labor resource allocation, labor structure

1. Introduction

In the context of global economic integration and the rapid development of the knowledge economy, talent resources and the innovation capacity of enterprises have become the core drivers of societal progress and economic growth. As China enters a stage of high-quality economic development, the 14th Five-Year Plan for National Economic and Social Development and the Long-Range Objectives Through the Year 2035 specifically highlights the need to improve talent strategy, deepen reforms in the talent development system, and reinforce the talent foundation for modernization. In response, local governments have actively implemented large-scale talent introduction initiatives since 2016, focusing on highly educated and skilled individuals. These policies have employed a variety of measures such as housing assistance, research funding, and tax incentives to cultivate a talent-friendly environment. Therefore, a comprehensive analysis of the effects and mechanisms through which local talent introduction policies influence enterprise innovation is of both theoretical and practical significance for shaping future talent strategies.

At present, talent introduction policies in China have evolved from traditional economic incentives—such as subsidies and tax breaks—to more comprehensive support systems

encompassing housing, education for children, and other aspects of daily life. For instance, in recent years, Shenzhen issued the Opinions of the CPC Shenzhen Municipal Committee and the Shenzhen Municipal Government on Strengthening the Construction of a High-Level Professional Talent Team (Shenfa [2008] No. 10), Hangzhou released the Implementation Opinions on Housing Security for High-Level Talent in Hangzhou (Office of the CPC Hangzhou Municipal Committee [2014] No. 77), and Beijing published the Administrative Measures for the Introduction of Graduates in Beijing (Beijing Human Resources and Social Security Bureau [2021] No. 22) to attract and retain talent. According to the Statistical Report on Talent Resources in the Beijing Region jointly released in 2023 by the Beijing Human Resources Research Center and the Beijing Talent Development Strategy Research Institute, the total number of talent resources in Beijing increased by 61,000 in 2023 compared to 2022, marking a growth of 0.8%.

A growing body of scholarly work has explored the impact of talent introduction policies on enterprise innovation. Sun Kunpeng and others have argued that such policies can stimulate R&D investment, patent output, and R&D efficiency within firms [1]. Li Xiaoping et al. believe that talent policies enhance regional innovation by increasing the stock and quality of human capital, alleviating corporate financing constraints, and reducing financial burdens associated with innovation [2]. Sun Wenhao has noted that these policies help address insufficient talent agglomeration and low innovation efficiency [3]. However, existing research primarily focuses on the overall effect of talent introduction policies on enterprise innovation, often emphasizing specific types of firms and typically measuring innovation through the number of granted patents. There is still a lack of in-depth analysis on how such policies influence different types of patents and how they impact the internal labor resource allocation of enterprises. To fill this gap, this study aims to explore in detail how talent introduction policies affect the optimization of internal talent structures in firms and examine their differentiated impact on various types of patents, thereby uncovering effective pathways to enhance enterprise innovation.

Using manually collected data on talent introduction policies issued across Chinese cities from 2016 to 2019, and employing a Difference-in-Differences (DID) approach that leverages the temporal and regional variation in policy implementation, this study makes the following marginal contributions: First, from the perspective of optimizing internal talent structures, it systematically examines two key pathways through which policy implementation enhances innovation: increasing the proportion of technical personnel and expanding the number of highly educated employees. This reveals the micro-level mechanism through which labor resource optimization promotes innovation. Second, it provides an in-depth analysis of the heterogeneous effects of talent introduction policies on different types of patent outputs. Third, it thoroughly investigates regional disparities in policy effects, as well as differential impacts on labor-intensive versus non-labor-intensive enterprises, technology-intensive versus non-technology-intensive enterprises, and manufacturing versus non-manufacturing sectors.

2. Mechanisms and research hypotheses

As a key driver of high-quality economic development, the factors influencing corporate innovation have garnered significant attention in academic research. However, the mechanisms by which talent policies impact corporate innovation remain inadequately understood. The effects of talent policies have been widely examined, showing multi-level characteristics. At the resource allocation level, Xiong Heping et al. confirmed that talent mobility policies help optimize interregional labor structure and allocation efficiency [4]. At the micro-level of firms, Sun Kunpeng et al. found that the intensity of policy subsidies is positively correlated with the increase in R&D personnel, and that lowering the policy threshold amplifies the policy effect [1]; Sun Zheyuan and Bai Yan revealed that urban policies facilitate the transformation of SMEs by alleviating financing constraints and optimizing human

capital [5]; Wei Xiahai et al. emphasized that the inflow of highly skilled talent and the enhancement of population diversity are important inducements for new business entry [6]; Ke Juan and Xu Zongwen focused on how policies promote dynamic adjustments in the internal talent structure of enterprises [7]. At the urban level, Ye Yang et al. confirmed a significant positive correlation between policy intensity and urban talent attractiveness [8]. Collectively, these studies systematically reveal the transmission mechanisms of talent policies in factor allocation, corporate behavior, and regional development.

Talent introduction policies play an important role in promoting corporate innovation, yet few studies have explored the mechanisms through which talent policies influence innovation from the perspective of labor resource allocation. Existing research on how talent policies drive corporate innovation presents a dual-path mechanism. On the direct path, Xie Xuemei and Sun Kunpeng confirmed that the agglomeration of high-end talent enhances R&D intensity and patent growth [1][9]; Xu Hongmei emphasized the effectiveness of policy support measures in western regions [10]; Hu Jun validated the spatial effects of urban policies [11]; Xu Daying revealed the competitive activation effect of optimizing human capital structure [12]. On the indirect path, Liu Chunlin focused on the resource integration function of policies [13]; Yu Minggui revealed that policies drive intelligent transformation through industrial robot investment [14]; Sun Wenhao demonstrated that structured policies outperform quantity-oriented ones in reconstructing innovation elements [3]. This paper finds, through literature review, that few studies have systematically discussed the mechanisms by which talent policies affect labor resource allocation. Accordingly, this study aims to explore the impact of talent policies on corporate innovation and the underlying mechanism of labor resource allocation, and proposes the following hypotheses:

Hypothesis 1: Talent introduction policies promote corporate innovation.

Drawing on the “capital–skill complementarity” theory cited by Yu Minggui and others [15–18], this study reveals that talent policies drive the flow of skilled labor through capital subsidies (such as tax incentives and housing support), thereby restructuring innovation elements within enterprises [11]. Research shows that highly skilled labor has strong complementarity with both physical capital (e.g., equipment, technology) and intangible capital (e.g., patents, experience) [9]: the former enhances equipment utilization efficiency, while the latter accelerates technological iteration and knowledge diffusion [2]. The increase in the proportion of skilled labor induced by policies not only improves the efficiency of R&D fund allocation [1] but also accelerates the reorganization of innovation elements through industrial agglomeration effects. Yu Minggui et al. further pointed out that this capital–skill synergy mechanism generates innovation momentum through labor structure optimization, confirming the structural transformation effect of policies on corporate innovation capacity [14]. Therefore, this study proposes:

Hypothesis 2: Local talent introduction policies enhance corporate innovation by optimizing the allocation of labor resources within firms.

Existing studies exhibit three main limitations: first, samples are often confined to firms of specific sizes or regions, limiting the generalizability of conclusions; second, innovation is typically measured using unidimensional indicators such as patents and R&D investment, raising questions about assessment validity; third, analysis of policy heterogeneity is inadequate, as it neither systematically compares interregional differences in policy implementation nor deeply examines the mediating effect of labor resource allocation. This paper breaks new ground by focusing on the perspective of labor factor reallocation and constructing a transmission framework of “policy incentives—human capital structure optimization—innovation element synergy.” It reveals that talent policies trigger a capital–skill complementary innovation mechanism by increasing the proportion of skilled labor. Its marginal contribution lies in verifying the mediating effect of labor resources and regional heterogeneity. This study aims to investigate the innovation effect of talent policies, with a particular

focus on the mechanism of labor resource allocation, thus offering both practical implications and marginal academic contributions.

3. Model design and data

Since talent introduction policies have been gradually implemented across cities starting in 2016, this study adopts a multi-period difference-in-differences (DID) model to evaluate the impact of such policies on corporate innovation capacity:

$$Patent_{i,c,t} = \beta_0 + \beta_1 Talent_{c,t} + \gamma control_{i,c,t} + \delta_t + \theta_c + \varepsilon_{i,c,t} \quad (1)$$

In Equation (1), i denotes individual firms, c denotes cities, and t denotes years.

$$LR_{it} = \alpha_0 + \alpha_1 Talent_{c,t} + \alpha control_{i,c,t} + \delta_t + \theta_c + \varepsilon_{i,c,t} \quad (2)$$

$$Patent_{i,c,t} = \varphi_0 + \varphi_1 Talent_{c,t} + \varphi_2 LR_{it} + \varphi_3 control_{i,c,t} + \delta_t + \theta_c + \varepsilon_{i,c,t} \quad (3)$$

Equations (2) and (3) are used to test the mediating mechanism. In both, i represents individual firms, c represents cities, and t represents years. δ_t and θ_c represent year and city fixed effects, respectively, and $\varepsilon_{i,c,t}$ is the error term.

The dependent variable in this study is corporate innovation capability, measured by patent stock (*Patent*), calculated as the annual sum of various types of patents for each company, including granted invention patents, published invention patents, utility model patents, and design patents. The independent variable is the talent introduction policy (*Talent*). It is assigned a value of 1 if the city implemented the policy in a given year, and 0 otherwise. The mediating variable is the firm's labour structure level (LR_{it}), measured by the proportion of technical personnel among employees and the number of employees with a bachelor's degree. Control variables include firm characteristics that influence innovation capability and outcomes, such as board size (*BoardSize*), proportion of independent directors (*IndDirectorRatio*), financing constraints (*SA*), firm size (*Size*), return on equity (*ROE*), and years listed (*ListAgee*).

Using the talent introduction policy as a quasi-natural experiment, this study manually collected policy data issued by various cities from 2016 to 2019. Sample data of A-share listed companies from 2013 to 2019 were obtained from the CSMAR database. Labour structure data were extracted from the employee structure section of the CSMAR database.

Table 1: descriptive statistics

Variable Name	Variable Symbol	Mean	Std. Dev.	Min	Max
Talent Introduction Policy	Talent	0.413	0.492	0	1
Patent Stock (10,000s)	Patent	162.558	1416.669	0	6.3652
Board Size	BoardSize	2.128	0.207	1.099	2.944
Independent Director Ratio	IndDirectorRatio	37.605	5.570	10	80
Financing Constraint	SA	-3.777	0.298	-5.543	-0.481
Return on Equity	ROE	0.041	1.660	-174.895	49.118
Firm Size	Size	22.236	1.510	14.942	31.036
Years Listed	ListAge	2.084	0.908	0	3.401
Proportion of Technicians (%)	M1	21.093	17.947	0.03	99.12
Number of Bachelor's Degree Holders (10,000s)	M2	1950.409	11207.84	2	25.193

4. Empirical results and analysis

4.1. Baseline regression

Table 2 reports the results of testing the impact of the talent introduction policy on firms' innovation capabilities. Column (1) presents the results of a univariate regression, while column (2) incorporates firm-level control variables. After controlling for city and year fixed effects, the coefficient of the talent policy variable (Talent) in column (1) is significantly positive at the 5% level, indicating that the average patent stock of firms in cities implementing the policy increased by 0.512. After adding control variables, the coefficient of (Talent) in column (2) rises to 0.735 and is significant at the 1% level, suggesting that the number of patent grants in these cities increased on average by 73.5%. This indicates that the talent introduction policy indeed enhances firms' innovation capability in the cities where it is implemented, as evidenced by a significant increase in patent stock, thus supporting Hypothesis H1.

Table 2: Baseline regression

	(1) patent	(2) patent
Talent	0.512** (0.2049)	0.735*** (0.2443)
Constant	1.549*** (0.0836)	52.107*** (19.2572)
Observations	18,839	17,105
Controls	NO	Yes
R-squared	0.7298	0.745
Controls	NO	YES
City FE	YES	YES
Year FE	YES	YES

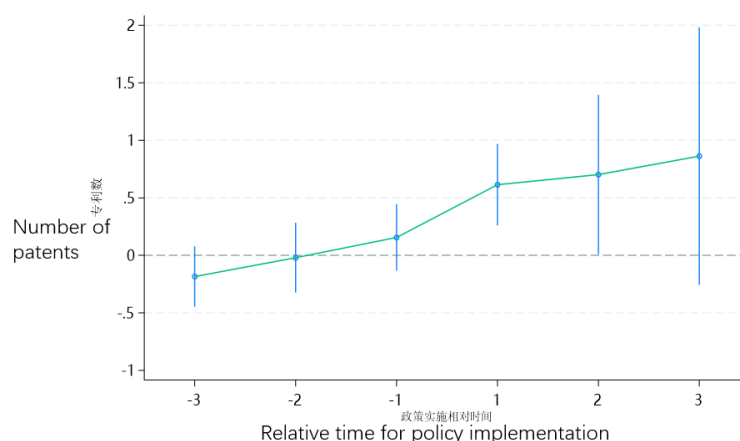


Figure 1: Parallel trend test

The above presents the parallel trend test for the DID model, indicating that the treatment and control groups satisfy the parallel trend assumption.

4.2. Robustness checks

4.2.1. Replacing the dependent variable

To test robustness, we replace the dependent variable with firms' R&D expenditure. Column (1) of Table 3 shows results without control variables; column (2) adds firm-level control variables. The findings are consistent with those of the baseline regression, supporting the hypothesis that the policy promotes firm innovation.

Table 3: Robustness checks

	(1) YFTR	(2) YFTR	(3) patent	(4) patent	(5) patent
Talent	0.756* (0.4374)	1.024** (0.4357)	0.654*** (0.2143)	0.723*** (0.2346)	0.542** (0.2135)
Constant	13.272*** (0.1895)	120.277*** (27.7522)	54.554*** (19.7728)	53.481*** (19.3253)	68.867*** (24.2544)
Observations	14,923	13,565	17,105	17,105	17,065
R-squared	0.8478	0.8779	0.7479	0.7460	0.7925
Controls	NO	YES	YES	YES	YES
City FE	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES

4.2.2. Adjusting model specifications

In column (3) of Table 3, city and year fixed effects are replaced with province-year interaction fixed effects while retaining city fixed effects, eliminating the influence of province and time trends on the estimation. Column (4) controls for industry fixed effects, year fixed effects, and city fixed effects. Column (5) controls for industry-year interaction fixed effects and retains city fixed effects. Across all three columns, the coefficient for Talent remains significantly positive, indicating the robustness of the conclusions.

4.3. Mechanism analysis

To further explore how the talent policy influences corporate innovation, this paper investigates whether it operates through optimizing internal firm talent structure—specifically by increasing the proportion of technical staff (M1) and expanding the number of highly educated employees (M2). The regression results are shown in the table below.

In column (1) of Table 4, after including control variables and fixed effects for city and year, the regression coefficient of Talent on the proportion of technical staff (M1) is 0.504, significant at the 10% level, indicating that the talent introduction policy significantly boosts the proportion of technical personnel. For every one-unit increase in policy intensity, the technical staff ratio increases by 50.4% on average. Column (2) examines the effect of the talent policy on firms' human capital structure. Using the number of employees with a bachelor's degree (M2) as the dependent variable, the coefficient for Talent is 0.895 and passes the 10% significance test, suggesting that the implementation of the policy significantly increases the number of highly educated employees in firms.

These results show that the talent introduction policy not only increases the proportion of technical staff in firms but also expands the number of highly educated employees, aligning with the hypothesized mechanism. In terms of policy impact, these two mechanisms together form a dual

pathway through which talent introduction enhances firm innovation—by optimizing the structure of professional talent to improve innovation efficiency and by elevating overall human capital to enhance innovation potential. This finding provides a new perspective for understanding the micro-level mechanisms of talent policy, highlighting that the effectiveness of such policies lies not only in directly attracting high-end talent but, more importantly, in driving the optimization of firms' entire labor structure.

Table 4: Mechanism test

	(1) M1	(2) M2
Talent	0.504* (0.2907)	0.895* (0.5432)
Constant	-14.898 (15.0742)	278.688*** (71.5869)
Observations	14,561	12,103
R-squared	0.8935	0.9742
Controls	YES	YES
City FE	YES	YES
Year FE	YES	YES

4.4. Heterogeneity

4.4.1. Heterogeneity in patent types

Table 5 presents the differentiated impact of the talent introduction policy (Talent) on various types of patent output. By conducting regression analyses on four categories of patents—granted invention patents, published invention applications, utility models, and design patents—the results reveal significant heterogeneity.

Column (1) of Table 5 displays the regression results for granted invention patents. The coefficient for Talent is 1.910 and significant at the 10% level, indicating that the policy has a significantly positive effect on high-quality patents that reflect technological breakthroughs and high market value. Column (2) shows the regression results for published invention applications; while the coefficient is positive, it is not statistically significant. The policy may incentivize firms to disclose technical solutions earlier, though disclosure decisions are influenced by complex factors such as technology disclosure strategies. Columns (3) and (4) show the coefficients for utility models and design patents, respectively, which are 0.314 and 0.117 and both statistically insignificant. This may suggest that the talent policy has a weaker impact on incremental innovations and is primarily effective in promoting breakthrough innovations.

Table 5: Heterogeneity analysis I

	(1) Invention Granted	(2) Invention Published	(3) Utility Model	(4) Design Patent
Talent	1.910* (1.1598)	3.144 (2.3770)	0.314 (1.3685)	0.117 (0.4050)
Observations	17,105	17,105	17,105	17,105
R-squared	0.9064	0.8500	0.8540	0.8442
City FE	YES	YES	YES	YES

Table 5: (continued)

Controls	YES	YES	YES	YES
Year FE	YES	YES	YES	YES

4.4.2. Labour-intensive vs. Non-labour-intensive enterprises

In labour-intensive enterprises, the implementation of the talent introduction policy does not significantly enhance firms' innovation capacity. As shown in column (1) of Table 6, the coefficient for the talent introduction policy variable is 0.061 and statistically insignificant. In contrast, for non-labour-intensive enterprises, the policy has a notable positive effect. Column (2) shows a coefficient of 1.055, which is significant at the 1% level. Non-labour-intensive enterprises generally have a stronger innovation foundation and resource allocation capacity, allowing them to provide high-end talent with broader development opportunities and innovation platforms. These firms often prioritise R&D and product innovation, enabling newly introduced talent to rapidly integrate into the innovation system, contribute novel technical ideas, and enhance the firm's innovation capacity.

Table 6: Heterogeneity analysis II

	(1) Labour-Intensive	(2) Non-Labour-Intensive	(3) Tech-Intensive	(4) Non-Tech-Intensive
Talent	0.061 (0.0634)	1.055*** (0.3674)	1.012** (0.4086)	0.366 (0.2614)
Observations	5,994	11,063	7,418	9,650
R-squared	0.7677	0.7488	0.7432	0.7828
City FE	YES	YES	YES	YES
Controls	YES	YES	YES	YES
Year FE	YES	YES	YES	YES

4.4.3. Technology-intensive vs. Non-technology-intensive enterprises

Column (3) of Table 6 shows a Talent coefficient of 1.012, significant at the 5% level, suggesting that the talent introduction policy significantly enhances innovation in technology-intensive enterprises. These enterprises typically possess a solid foundation in innovation and R&D capabilities, enabling them to fully leverage the expertise and creative capacities of high-end talent and convert their knowledge into tangible innovation outcomes, thereby increasing the firm's patent stock. For non-technology-intensive enterprises, however, the policy's impact is smaller and not statistically significant. Column (4) shows a coefficient of only 0.366 for the Talent variable, which is not significant. This implies that the policy's role in promoting innovation is limited in non-technology-intensive firms, possibly due to their weaker innovation foundations and inability to fully utilise the innovation potential of high-end talent.

5. Conclusion and policy implications

The findings of this study are as follows: the talent introduction policy significantly increased the patent stock of firms in policy-implementing cities and also stimulated higher R&D investment among those firms. Mechanism testing indicates that the policy attracts talent to local firms, increases the proportion of technical and highly educated personnel, and optimises firms' labour allocation. This study further examines the heterogeneity of the policy's effects from both the patent-type and

firm-level perspectives. The results show clear variation across different patent types: the policy significantly promotes high-quality patents with strong technical and market value, while its impact on incremental innovation is limited, with the policy effects mainly concentrated in breakthrough innovations. At the firm level, the policy has a significantly positive effect on innovation capacity in non-labour-intensive, technology-intensive, and manufacturing firms, while the impact is relatively limited in labour-intensive, non-technology-intensive, and non-manufacturing firms.

However, this study also has several limitations. It faces two constraints: (1) a limited time frame (2016-2019), which restricts the ability to assess long-term policy effects; and (2) potential quality mismeasurement in patent stock (e.g., strategic applications for utility model patents) and incomplete data coverage. Nevertheless, the mechanism through which labour allocation optimisation promotes innovation has been verified. Future research should aim to expand the temporal scope and adopt a multidimensional innovation evaluation framework for deeper analysis.

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