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The Impact of Human Capital Accumulation and Technological Innovation on the Improvement of Regional New Quality Productivity

Yuyan Tan*

School of Philosophy and Law and Politics, Shanghai Normal University, Shanghai 200234, China

**Corresponding author: Yuyan Tan, E-mail: 1000549292@smail.shnu.edu.cn.*

Abstract

Against the backdrop of a new round of technological revolution and industrial transformation, new-quality productivity, as advanced productivity driven by innovation and low-carbon greening, is highly important for promoting high-quality economic development. This article theoretically summarizes the impact logic of human capital accumulation and technological innovation on new quality productivity and uses a double difference model to empirically analyse the impact of human capital accumulation on regional new quality productivity by using urban talent introduction policies as quasi natural experimental identification variables. Research has revealed that (1) the implementation of talent introduction policies has a significant positive effect on new-quality productivity, verifying the importance of human capital accumulation for high-quality economic development. (2) Human capital enhances the level of regional new-quality productivity by influencing technological innovation. (3) Heterogeneity test results reveal that groups with high fiscal self-sufficiency rates, high talent scales, and developed cities have a stronger promoting effect on human capital accumulation, and the more complete the supporting measures of urban talent introduction policies are, the more significant their promoting effect. (4) Considering the factors of policy synergy, the accumulation of human capital and technological innovation have jointly promoted the improvement of regional new-quality productivity. Finally, corresponding policy recommendations were proposed for improving talent introduction policies, promoting regional technological innovation and development, and enhancing policy evaluation and dynamic adjustment mechanisms.

Keywords

new quality productivity, human capital, technological innovation, high-quality development

1. Introduction

With the deepening of a new round of scientific and technological revolution and industrial transformation, human productive forces are undergoing unprecedented and profound changes. During his inspection in Heilongjiang, President Xi Jinping for the first time proposed the important concept of “new quality productive forces,” providing clear guidance for understanding and grasping emerging trends and characteristics in the development of productive forces (Xi, 2024). New quality productive forces represent an advanced form of productivity characterized by innovation-driven growth and green, low-carbon development. They are a key driver in facilitating industrial restructuring and building a modern economic system (Ren & Gong, 2024; Shi, 2024). Compared with traditional economic growth models, new quality productive forces focus not only on quantitative expansion but also on improving the quality and efficiency of production, thereby ensuring sustainable enhancement in the quality of economic growth (Ren et al., 2024).

Centering on high-level production factors such as knowledge, technology, and digital information, new quality productive forces embody a shift from a resource-input-oriented model to a quality- and efficiency-oriented development paradigm (Xue et al., 2024). Against this backdrop, human capital and technological innovation—two core driving forces—play pivotal roles. On the one hand, the accumulation of human capital provides the intellectual and knowledge foundation for breakthrough innovations (Liu, 2024); on the other hand, the development and application of emerging technologies significantly broadens the scope for human capital utilization, creating new opportunities for its empowerment (Wang & Cao, 2024). Therefore, an in-depth exploration of the driving effects of human capital accumulation and technological innovation on the enhancement of new quality productive forces is of significant theoretical and practical relevance for meeting the evolving requirements of China's modernization agenda.

Most existing studies remain at the level of theoretical discussion. To address this gap, this paper combines theoretical analysis with empirical investigation to clarify the effects of human capital accumulation and technological innovation on new quality productive forces, with the aim of providing valuable insights for policy formulation. Specifically, the study is organized around three objectives. First, at the theoretical level, it reviews the underlying mechanisms through which human capital accumulation and technological innovation affect new quality productive forces, thereby laying a foundation for subsequent empirical analysis. Second, at the empirical level, it employs a difference-in-differences (DID) approach to address endogeneity concerns and identify the causal effects of human capital accumulation and technological innovation on new quality productive forces. Third, the empirical findings offer targeted policy recommendations to promote human capital accumulation, stimulate technological innovation, and enhance new quality productive forces.

The remainder of this paper is structured as follows: Section 2 presents the mechanism analysis; Section 3 outlines the empirical research design; Section 4 reports the empirical results; Section 5 provides further extensions; and Section 6 concludes with policy implications.

2. Mechanism Analysis

As a critical component of factor endowment structure, the accumulation of human capital profoundly affects the development of new quality productive forces by fostering technological innovation. This mechanism reflects the close interconnection among human capital accumulation, technological innovation, and new quality productive forces, forming the core analytical framework of this study.

Although few studies have directly examined the influence of the human capital structure and technological innovation on new quality productive forces, insights can be drawn from traditional urban economic growth theories. Specifically, prior studies shed light on the role of human capital accumulation in driving technological innovation, its relationship with industrial upgrading, and its spillover effects, as well as the mechanisms through which technological innovation promotes economic development and enhances productivity. Building on these theoretical foundations, this paper explores the following three questions: (1) How does human capital accumulation improve the level of new quality productive forces in a region? (2) In what ways does technological innovation contribute to the enhancement of new quality productive forces? (3) How does human capital accumulation promote new quality productive forces by influencing technological innovation?

2.1 Human Capital Accumulation and New Regional Quality Production Forces

The impact of human capital on economic growth has long been a central topic in economics. Existing studies suggest that a highly skilled workforce not only directly increases labor productivity but also indirectly stimulates economic development through innovation and technological progress. From this perspective, the contribution of human capital accumulation to regional new quality productive forces can be understood in several ways:

The first is the enhancement of knowledge and skills. Human capital accumulation entails investment in education, training, and career development, which elevates the knowledge base and skill levels of the workforce. This, in turn, increases the efficiency of production processes (Huang et al., 2013). Highly skilled workers are better able to utilize technology effectively, improving productivity and driving the advancement of new quality productive forces. Second, the innovation capacity should be strengthened. The concentration of highly skilled talent facilitates technological innovation, product development, and market expansion, thereby boosting regional competitiveness. Third, transformation of production modes is needed. Human capital accumulation encourages a shift toward knowledge-intensive and technology-intensive production structures, increasing efficiency and product value added, thus fostering the development of new quality productive forces.

For example, according to the 14th Five-Year Plan for Scientific and Technological Innovation in Jiangsu Province, during the 13th Five-Year Plan period, Jiangsu's research and development (R&D) expenditure as a share of GDP rose to 2.85%, and the number of invention patents per 10000 people reached 36.1—approaching the median level of innovation-oriented economies. This illustrates the significant role that human capital and innovation capacity play in driving productivity growth.

On the basis of the above analysis, highly skilled human capital—through knowledge and skill enhancement, strengthened innovation capacity, and industrial structural transformation—effectively supports the growth of regional new quality productive forces.

Hypothesis 1: The agglomeration of human capital is conducive to improving the level of regional new quality productive forces.

2.2 Technological Innovation and Regional New Quality Productive Forces

According to endogenous growth theory, technological innovation—by enhancing the efficiency of production factors and improving resource allocation efficiency—serves as a key mechanism for sustaining long-term economic growth. A review of existing empirical findings suggests that technological innovation contributes to the enhancement of regional new quality productive forces in several ways:

First, total factor productivity (TFP) should be improved. Technological innovation significantly increases TFP, which is a core manifestation of the advancement of new quality productive forces. Studies have shown that R&D investment and technological innovation can markedly increase TFP, thereby driving economic growth (Griliches, 1973; Luintel & Khan, 2011). In this process, new production technologies and processes are continuously introduced, leading to substantial improvements in production efficiency. Second, the industrial structure should be optimized. Technological innovation facilitates industrial upgrading by enabling the adoption of advanced production methods and management models in traditional sectors. This fostered a transition from low value-added activities to high value-added activities (Song & Peng, 2019). The expansion of high-tech industries not only supports economic transformation but also provides a solid foundation for the improvement of new quality productive forces. Third, resource allocation efficiency should be enhanced. By altering the marginal productivity of production factors, technological innovation improves the efficiency of resource allocation. As resources flow toward industries and firms with higher productivity, the microlevel allocation of factors becomes more efficient, thereby increasing macrolevel economic output.

Evidence from prior studies indicates that technological innovation not only directly advances new quality productive forces but also promotes long-term economic development through industrial restructuring and more efficient resource allocation.

Hypothesis 2: Technological innovation contributes to the improvement of regional new quality productive forces.

2.3 Human Capital Accumulation, Technological Innovation, and New Quality-Productive Forces

Human capital accumulation promotes technological innovation, which in turn drives the advancement of new quality productive forces. The improvement in new quality productive forces subsequently stimulates higher levels of human capital accumulation and technological innovation. This mutually reinforcing cycle constitutes a central engine for high-quality regional economic development.

However, existing studies examining the relationships among human capital accumulation, technological innovation, and local development often treat these elements in isolation, overlooking their inherent interconnections. Some research has focused on the direct impact of human capital on economic growth (Zhong & Li, 2009), whereas other studies have emphasized the role of technological innovation in driving economic development (Galor & Weil, 2000; Nelson & Phelps, 1966). Few studies have systematically investigated the mediating mechanism through which human capital accumulation affects new quality productive forces via technological innovation. To address this gap, the present study integrates two perspectives to explore the intrinsic linkages between human capital accumulation, technological innovation, and new quality productive forces.

Specifically, the relationship between human capital and technological innovation can be analysed in three dimensions:

The first is the interactive dynamics between human capital and technological innovation. Highly skilled human capital possesses stronger learning capabilities and absorptive capacity for new technologies, accelerating the diffusion and application of innovations. This, in turn, fosters further accumulation of human capital. The second is the alignment between the human capital structure and industrial upgrading. A dynamic matching relationship exists between an optimized human capital structure and industrial upgrading (Acemoglu & Zilibotti, 2001). The agglomeration of advanced human capital drives the shift from labor-intensive industries to knowledge- and technology-intensive industries. This transformation, in turn, demands greater input of high-caliber human capital, thereby further stimulating technological innovation and enhancing new quality productive forces (Dai et al., 2020). Third, spillover effects and knowledge diffusion. Highly skilled human capital generates positive externalities by disseminating professional knowledge and skills to other workers, thereby improving the overall technological level (Liu et al., 2023). Such knowledge diffusion not only promotes technological innovation but also accelerates the commercialization of scientific and technological achievements, enabling firms to increase production efficiency through the application of new technologies, which ultimately advances new quality productive forces.

By 2022, Jiangsu Province had achieved 50.4 invention patents per 10,000 people—among the highest in the nation—and an R&D expenditure intensity of 3% of GDP. These figures illustrate how human capital accumulation, by fostering technological innovation, can significantly enhance regional new quality productive forces. This process depends not only on attracting and cultivating highly skilled human capital but also on industrial structure optimization and improved resource allocation efficiency.

Hypothesis 3: Human capital accumulation enhances regional new-quality productive forces by influencing technological innovation.

3. Empirical Research Design

3.1 Model Specification

To empirically examine whether human capital agglomeration and technological innovation promote the development of regional new quality productive forces, this study employs a difference-in-differences (DID) framework. Specifically, the implementation of city-level talent introduction policies is treated as an exogenous shock to human capital accumulation, allowing us to identify its causal effect on local new quality productive forces.

Furthermore, following the two-step mediation analysis approach, we investigate the mechanism through which human capital agglomeration and technological innovation jointly affect the level of new quality productive forces. The baseline econometric specification is expressed as follows:

$$NP_{it} = \beta_0 + \beta_1 Hc_{it} + \beta_k CVs_{it} + \mu_t + v_i + \varepsilon_{it}$$

$$Ti_{it} = \beta_0 + \beta_1 Hc_{it} + \beta_k CVs_{it} + \mu_t + v_i + \varepsilon_{it}$$

where i indexes cities and t indexes years; NP_{it} denotes the new quality productive forces index for city i in year t; Hc_{it} is a binary variable indicating whether city i has implemented a "talent introduction" policy in year i; Ti_{it} captures the level of technological innovation in city i in year i; CVs_{it} represents a vector of control variables; μ_t and v_i denote time and city fixed effects, respectively, controlling for unobserved factors varying across time or across cities; and ε_{it} is the idiosyncratic error term.

3.2 Variable Selection and Descriptive Statistics

In this study, the dependent variable is new quality productive forces (NQPF). As emphasized by General Secretary Xi Jinping, the defining characteristic of the NQPF is innovation-driven development, whereby technological innovation catalyzes industrial innovation, enabling the economy to transcend traditional growth modes and productivity pathways. The NQPF is characterized by high technology intensity, high efficiency, and high quality, which is consistent with the vision of advanced productive forces under the new development paradigm.

Existing studies have explored various approaches to measuring NQPF. At the provincial level, Han et al. (2024) proposed a measurement framework distinguishing between physical and penetrative elements. At the city level, Zhao et al. (2024) measured NQPF from the perspectives of technological productivity, green productivity, and digital productivity. Building on these prior contributions and integrating the theoretical insights from General Secretary Xi's characterization of the NQPF, this paper proposes a more comprehensive measurement framework.

Specifically, our NQPF index comprises five dimensions: technological productivity, green productivity, inclusive productivity, digital productivity, and innovative productivity. This multidimensional framework encapsulates both the technology-driven and innovation-led attributes of the NQPF while also aligning with the strategic objective of transcending traditional growth models to pursue high-technology, high-efficiency, and high-quality development. The detailed indicator system is presented in Table 1.

In multicriteria comprehensive evaluations, the determination of indicator weights is a critical methodological issue. Traditional subjective weighting approaches—such as expert scoring or analytic hierarchy processes—are often criticized for their inherent arbitrariness, susceptibility to randomness, and potential redundancy of information among indicators. To address these limitations, the entropy weight method (EWM) has been developed. Rooted in the principles of information theory, the EWM objectively determines indicator weights on the basis of the degree of variation observed across samples. The smaller the information entropy of an indicator is, the greater the amount of information it conveys; consequently, its role in the comprehensive evaluation is more significant, and its weight should be correspondingly greater. Owing to its simplicity, objectivity, scientific rigor, and broad applicability, the EWM has been widely adopted across diverse research domains. In this study, the EWM is employed to determine the weights within the novel productivity indicator system, thereby enhancing the robustness and credibility of the evaluation results (Lang et al., 2023).

3.2.1 Explanatory Variables

To address the potential endogeneity between human capital accumulation, technological innovation, and new quality productive forces (NQPF), and following Jin and Zhang (2024), this study exploits the fact that the timing of talent introduction policy implementation varies across Chinese cities. We treat the introduction of such policies as an exogenous shock and apply a multiperiod difference-in-differences (DID) approach, using the implementation of local talent introduction policies as a quasi natural experiment to measure the level of human capital accumulation in each city. The policy introduction dates were obtained manually by visiting the official websites of local Human Resources and Social Security Bureaus and searching for keywords such as "talent settlement" (*rencai luohu*), "talent introduction" (*rencai yinjin*), and "talent support" (*rencai baozhang*). The first appearance date of a city's talent introduction policy was recorded as its implementation time.

3.2.2 Mediating Variable

Given that the level of technological innovation is closely tied to the human capital gains brought by talent introduction policies and drawing on Zhao (2022), this study measures local technological innovation using the number of granted patents in each city. To address scale differences and skewness in the data, the patent count is transformed via the natural logarithm of *(patent count + 1)*.

Table 1: Measurement Framework for New Quality Productive Forces (NQPF)

Category Indicator	Sub-Indicator	Specific Indicator	Unit	Indicator Direction	
				+	−
Technological Productivity	Science & Technology Investment	Technology investment/Fiscal expenditure	%	√	
		Expenditure on new technology transformation	%	√	
	Science & Technology Output	Number of granted patents	Unit	√	
	Standard of Living	Per capita disposable income	CNY	√	
	Industrial structure	Proportion of tertiary industry	%	√	
	Overview of Foreign Investment	Utilization of foreign capital	Billion USD	√	
	Overview of Foreign Enterprises	Total output value of foreign-funded enterprises	100 million CNY	√	
		Number of foreign-funded enterprises	Unit	√	
Green Productivity	Environment	Industrial wastewater discharge per industrial output value	Tons/10000 CNY		√
	Exhaust emissions	Industrial sulfur dioxide emissions/Industrial output value	Tons/10000 CNY		√
		Industrial smoke (powder) dust emissions/Industrial output value	Tons/10000 CNY		√
	Green conversion efficiency	Comprehensive utilization rate of general industrial solid waste	%	√	
		Centralized treatment rate of sewage treatment plant	%	√	
		Harmless treatment rate of household waste	%	√	
Inclusive Productivity	Social Welfare	Number of physicians/population	Unit/10000 persons	√	
		On duty employee salary	CNY	√	
		Urban greening rate	%	√	
	Consumption Level	Social retail consumption/GDP	%	√	
Digital Productivity	Telecommunications business communication	Total telecommunications business volume	10000 CNY	√	
	Internet penetration	Number of Internet users	Unit	√	
	Development of the digital industry	Number of employees in information transmission computer services and software industry	10000 persons	√	
	Digital Employment Concept	Proportion of employees in the tertiary industry	%	√	
Innovative Productivity	Technical research and development(R&D)	Number of high-tech R&D personnel	Person	√	
		Number of high-tech research and	Unit	√	

		development institutions			

3.2.3 Control Variables

To more accurately estimate the net effect of the core explanatory variables, we follow Han et al. (2024) and Zhao et al. (2024) in selecting the following control variables: ① the GDP growth rate – captures overall economic conditions; ② the proportion of secondary industry value added – controls for industrial structure effects; ③ the unemployment rate – reflects labor market conditions; ④ the scale of fixed asset investment – measures the impact of capital inputs; ⑤ the scale of local government expenditure – accounts for the role of fiscal policy; ⑥ the scale of local government education expenditure – indicates human capital investment; ⑦ population density – controls for demographic distribution differences; ⑧ the loan-to-deposit ratio – proxies for financial market activity; and ⑨ the proportion of higher-education students enrolled – measures the prevalence of higher education.

The data sources include the *China City Statistical Yearbook*, various provincial and municipal statistical yearbooks, and official websites of local statistical bureaus. Missing data were imputed via linear interpolation; observations with missing values that could not be imputed were excluded. The final sample consists of 3458 valid observations covering the period 2010–2022. The specific calculation methods for each variable are shown in Table 2.

Table 2: Variables and Measurement Methods

Variable	Symbol	Measurement
New-quality Productivity	NP	Index System Measurement
Human Capital Agglomeration	HC	Regional Talent Introduction Policy
Technological Innovation	TI	Ln (Number of Urban Patent Authorizations + 1)
GDP Growth Rate	GDPG	(Current Year GDP-Previous Year GDP)/Previous Year GDP
Proportion of Added Value of Secondary Industry	GDP2	Proportion of Added Value of Secondary Industry to GDP
Unemployment Rate	Unemployment	Number of Unemployed Persons/Total Population
Fixed-asset Investment Scale	Invest	Proportion of Fixed-asset Investment Scale to GDP
Local Government Expenditure Scale	Gov	Proportion of Local Government Expenditure Scale to GDP
Local Government Education Expenditure Scale	GovE	Proportion of Local Government Education Expenditure Scale to GDP
Population Density	PD	Permanent Resident Population/Administrative Region Area
Loan-to-Deposit Ratio	DLR	Regional Deposit Scale/Loan Scale
Proportion of Enrolled Higher-education Students	HE	Number of Regional Students in Junior College and Above/Permanent Resident Population

The calculation methods and descriptive statistics for all the variables are presented in Table 3. As shown, the novel productivity index comprises 3458 observations, with a mean value of 0.005, a standard deviation of 0.014, a minimum of 0, and a maximum of 0.139. The mean values for technological innovation and talent introduction are 7.562 and 0.632, respectively, with corresponding standard deviations of 1.730 and 0.482.

Table 3: Descriptive Statistics of the Variables

Variable	Symbol	Obs	Mean	Std0. Dev0.	Min	Max
New-quality Productivity	NP	3458	0.005	0.014	0	0.139
Human Capital Agglomeration	HC	3458	0.632	0.482	0	1
Technological Innovation	TI	3458	7.562	1.730	0	12.540
GDP Growth Rate	GDPG	3458	0.089	0.041	-0.039	0.182
Proportion of Added Value of Secondary Industry	GDP2	3458	0.458	0.107	0.165	0.725
Unemployment Rate	Unemployment	3458	0.006	0.005	0.001	0.024
Fixed-asset Investment Scale	Invest	3458	0.852	0.403	0.036	2.622
Local Government Expenditure Scale	Gov	3458	0.186	0.08	0.075	0.717
Local Government Education Expenditure Scale	GovE	3458	0.032	0.013	0.013	0.123

Population Density	PD	3458	0.045	0.031	0.001	0.144
Loan-to-Deposit Ratio	DLR	3458	0.696	0.192	0.306	1.263
Proportion of Enrolled Higher-education Students	HE	3458	0.022	0.027	0.001	0.119

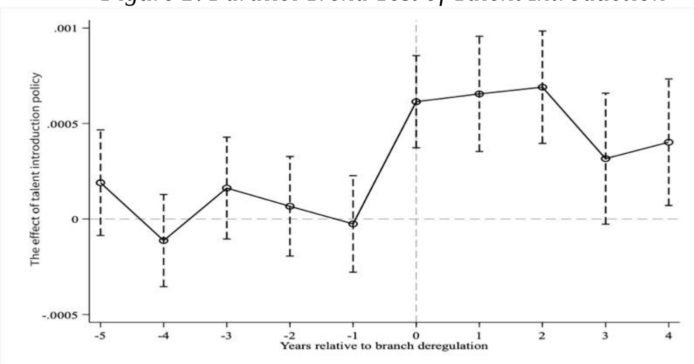
3.3 Parallel Trend Test

To verify the core assumption underlying the difference-in-differences (DID) methodology, a parallel trend test was conducted. Following the regression procedure, the novel productivity index was used as the dependent variable, whereas the interaction terms between the year dummy variables and the treatment variable served as the key independent variables. The estimated coefficients represent the magnitude of differences across year groups. The regression specification and corresponding results are presented below.

$$NP_{it} = \alpha_1 + \sum_{t=2010}^{2022} \beta_{1t} \times Ti \times Year_t + \delta_1 \times Control_t + \lambda_i + \lambda_t + \varepsilon_{it}$$

Figure 1 shows the estimated coefficients of the talent introduction policy effect for each year relative to the policy implementation year, along with their corresponding confidence intervals. The vertical axis represents the estimated effect of the talent introduction policy, and the horizontal axis denotes the time relative to the year of policy implementation. The parallel trend assumption requires that, prior to policy implementation, the treatment and control groups exhibit similar trends—i.e., the estimated coefficients before the policy should be close to zero and exhibit no statistically significant variation.

Figure 1: Parallel Trend Test of Talent Introduction



As shown in Figure 1, during the prepolicy period (years −5 to −1), the estimated coefficients of the talent introduction policy fluctuate around zero, with most confidence intervals crossing the zero line and exhibiting no statistically significant differences. This finding indicates that prior to policy implementation, there were no significant disparities in the policy effects across regions. In other words, the treatment and control groups followed similar trends in terms of talent introduction effects before the policy, thereby satisfying the parallel trend assumption and ensuring the validity of the DID estimation.

4. Empirical Analysis

4.1 Baseline Regression Results

This study employs a difference-in-differences (DID) framework to examine the impact of talent introduction policies on regional new-quality productivity. As reported in Table 4, the regression results indicate that the talent introduction policy significantly enhances new-quality productivity. Across Models 1 through 5, the estimated coefficients of the policy variable are 0.00069, 0.00068, 0.00068, 0.00068, and 0.00069, respectively, all of which are statistically significant at the 1% level. These results suggest that the implementation of talent introduction policies has a substantial positive effect on the improvement of regional new-quality productivity, thereby validating the hypothesis that talent agglomeration drives productivity upgrading.

Furthermore, a regression analysis based on Model 2 is conducted to assess the effect of the talent introduction policy on regional technological innovation. As shown in Table 5, the estimated coefficients of the policy variable range from 0.00652--0.00932 across Models 1--5, all of which are statistically significant at the 5% level. These findings indicate that the implementation of the talent introduction policy substantially enhances regional technological innovation. This result supports the proposed mechanism whereby human capital accumulation promotes new-quality productivity through its positive impact on technological innovation.

4.2 Placebo Test

Another concern regarding the identification assumption of the DID method is the potential influence of other unobservable city characteristics that vary over time and may affect the results. Cities differ in many respects. Although the regressions above have incorporated city fixed effects to control for all time-invariant characteristics that might affect new-quality productivity, some characteristics may have time-varying impacts that could undermine the identification assumption, and these effects cannot be fully controlled by the model.

To address this issue, this study first controls for a set of observable major city characteristics, including the GDP growth rate, the share of secondary industry value added, the scale of fixed asset investment, local government education expenditure, local government total expenditure, population density, the loan-to-deposit ratio, the unemployment rate, and the proportion of enrolled higher education students. However, it is impossible to control for all characteristics, especially unobservable ones.

Accordingly, an indirect placebo test is conducted. From the following expression, the coefficient $\hat{\beta}$ can be written as:

$$\hat{\beta} = \beta + \gamma \times \frac{cov(\text{Treat}_{it}, \varepsilon_{it} \mid W)}{var(\text{Treat}_{it} \mid W)}$$

where W includes all other control variables and fixed effects, and γ represents the effect of unobserved factors on the dependent variable. If γ=0, unobserved factors do not affect the estimation results, indicating that β is unbiased. This, however, cannot be directly verified. Therefore, the logic of the indirect placebo test is to replace Treat $_{it}$ with a fictitious variable that, in theory, should have no impact on the dependent variable. Since it is randomly generated, the true coefficient should be β=0. If the estimated coefficient $\hat{\beta}$ of this fictitious variable is found to be nonzero, it would indicate model misspecification and suggest that other characteristics may bias the estimates.

Table 4: Baseline Regression Results of the Talent Introduction Policy

	(1)	(2)	(3)	(4)	(5)
	New-quality Productivity	New-quality Productivity	New-quality Productivity	New-quality Productivity	New-quality Productivity
Talent introduction policy	0.00069***	0.00068***	0.00068***	0.00068***	0.00069***
	(0.00025)	(0.00025)	(0.00025)	(0.00025)	(0.00025)
GDP growth rate		0.00406*	0.00326	0.00327	0.00331
		(0.00238)	(0.0022)	(0.0022)	(0.00207)
Proportion of added value of the secondary industry		0.00089	0.00052	-0.00019	-0.00127
		(0.00094)	(0.00096)	(0.00125)	(0.00137)
Unemployment rate			-0.05276*	-0.05276*	-0.04299
			(0.02998)	(0.03007)	(0.02924)
Fixed-asset investment scale			-0.0012***	-0.00121***	-0.00125***
			(0.00035)	(0.00036)	(0.00036)
Local government expenditure scale				-0.00435***	-0.00391***
				(0.00153)	(0.00146)
Local government education expenditure				0.01028	0.0024

scale					
				(0.01216)	(0.01253)
Population density					0.08969**
					(0.03779)
Loan-to-deposit ratio					-0.00013
					(0.00081)
Proportion of enrolled higher-education students					-0.00208
					(0.00587)
_cons	0.00479***	0.00403***	0.00563***	0.00644***	0.00317*
	(0.00016)	(0.00043)	(0.00054)	(0.00098)	(0.0019)
City fixed effects	YES	YES	YES	YES	YES
Time fixed effects	YES	YES	YES	YES	YES
Observations	3458	3458	3458	3458	3458
R-squared	0.98435	0.98441	0.9849	0.98498	0.98534

Standard errors are in parentheses.
*** p<0.01, ** p<0.05, * p<0.1.

Table 5: Mechanistic Test

	(1)	(2)	(3)	(4)	(5)
	Technological Innovation	Technological Innovation	Technological Innovation	Technological Innovation	Technological Innovation
Talent introduction policy	0.00652**	0.00821**	0.00932**	0.00795***	0.00697**
	(0.00265)	(0.00324)	(0.00423)	(0.00212)	(0.00313)
GDP growth rate		1.14402**	1.14335**	1.12786**	1.12432**
		(0.50952)	(0.49984)	(0.49788)	(0.50854)
Proportion of added value of the secondary industry		0.05179	0.04421	0.44023	0.3351
		(0.43798)	(0.44018)	(0.44282)	(0.45508)
Unemployment rate			4.4222	4.73171	4.93118
			(6.59741)	(6.67689)	(6.60886)
Fixed-asset investment scale			-0.05149	-0.02962	-0.03094
			(0.08508)	(0.08606)	(0.08564)
Local government expenditure scale				0.46223	0.50503
				(1.15027)	(1.12633)
Local government education expenditure scale				6.12862	5.59359
				(5.55271)	(5.60675)
Population density					6.41666
					(4.41169)
Loan-to-deposit ratio					-0.03231
					(0.23598)
Proportion of enrolled higher-education students					1.85507
					(2.46998)
_cons	7.56689***	7.44273***	7.4631***	6.98039***	6.73147***
	(0.0396)	(0.19936)	(0.2234)	(0.3331)	(0.39535)
City fixed effects	YES	YES	YES	YES	YES
Time fixed effects	YES	YES	YES	YES	YES
Observations	3458	3458	3458	3458	3458
R-squared	0.93276	0.93299	0.93307	0.93352	0.9337

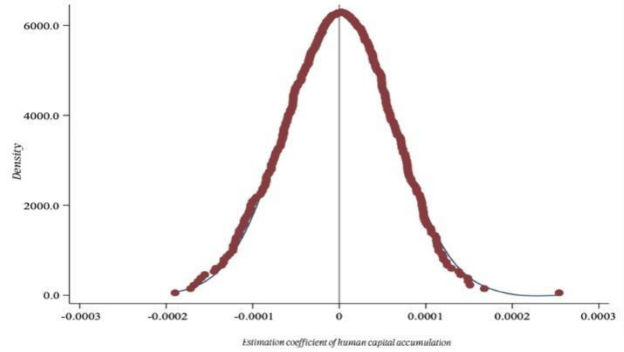
Standard errors are in parentheses.
*** p<0.01, ** p<0.05, * p<0.1.

Figure 2 presents the placebo test results for the implementation of the talent introduction policy, evaluating the robustness of its effect on new-quality productivity. The vertical axis represents density, and the horizontal axis represents the estimated coefficient of human capital accumulation. The placebo test is conducted by randomly assigning fictitious policy implementation years to test the authenticity of the actual policy effect. Under the random assignment hypothesis, the estimated values are expected to be concentrated around zero, thereby ruling out interference from other unobserved factors. As shown in Figure 2, the estimates approximate a normal distribution, with most values clustered near zero. This result indicates that when the policy implementation time is randomly assigned, the estimated coefficients do not deviate significantly from zero, further confirming that prior to actual policy implementation, changes in new-quality productivity across regions are not systematically biased by other unobserved factors.

4.3 Robustness Test

To further substantiate the robustness of the empirical results, this study employs three complementary approaches: subindicator regressions, substitution of the dependent variable, and the propensity score matching–difference-in-differences (PSM–DID) method.

Figure 2: Placebo Test for the Talent Introduction Policy



4.3.1 Subindicator Regression Results

Given that a universally accepted framework for measuring new-quality productivity has yet to be established and that the composite index integrates multiple subdimensions, this study further refines the analysis by conducting regressions on each secondary indicator separately. This approach is particularly relevant because talent introduction policies may directly affect the number of scientific and technical personnel—a core element of innovation productivity. By disaggregating the analysis, we ensure that the robustness of the results is maintained while avoiding potential bias in causal inference for the overall index that could arise from the influence of a single secondary indicator.

Table 6: Subindex Regression Results

	(1) Technology Productivity	(2) Green Productivity	(3) Inclusive Productivity	(4) Digital Productivity	(5) Innovative Productivity
Talent introduction policy	0.01012**	0.02546**	0.00798**	0.0568**	0.00283**
	(0.00432)	(0.01139)	(0.00349)	(0.02316)	(0.00141)
GDP growth rate	-0.05754***	-0.07552	-0.02123	-0.15912	-0.01356**
	(0.02068)	(0.05816)	(0.01677)	(0.11327)	(0.00625)
Proportion of added value of the secondary industry	0.10724***	0.33508***	0.06076***	0.55827***	0.02708***
	(0.02258)	(0.06028)	(0.01656)	(0.12223)	(0.00683)
Unemployment rate	-0.74206**	-1.92092**	-0.64653**	-3.80573*	-0.2216*
	(0.37257)	(0.92945)	(0.30262)	(2.09313)	(0.12133)
Fixed-asset investment scale	0.0026	-0.00213	0.00146	0.00028	-0.00006

	(1) Technology Productivity	(2) Green Productivity	(3) Inclusive Productivity	(4) Digital Productivity	(5) Innovative Productivity
	(0.00394)	(0.00926)	(0.00316)	(0.02032)	(0.00129)
Local government expenditure scale	-0.03398**	-0.07387	-0.01598	-0.13501	-0.00622
	(0.01609)	(0.04816)	(0.01379)	(0.08621)	(0.00473)
Local government education expenditure scale	0.93167***	2.2456***	0.42605***	3.94943***	0.23302***
	(0.18021)	(0.47838)	(0.1454)	(1.0309)	(0.05975)
Population density	1.80837***	3.74417***	1.25294***	9.12328***	0.54304***
	(0.51992)	(1.18378)	(0.41908)	(2.6928)	(0.1599)
Loan-to-deposit ratio	0.02792***	0.05947***	0.02465***	0.15187***	0.00684**
	(0.00888)	(0.02197)	(0.00705)	(0.04898)	(0.00268)
Proportion of enrolled higher-education students	-0.07174	-0.2286	-0.07282	-0.50476	-0.02736
	(0.09668)	(0.26811)	(0.08094)	(0.55066)	(0.03018)
_cons	-0.15057***	-0.27511***	-0.06795***	-0.68969***	-0.03952***
	(0.02817)	(0.06343)	(0.0218)	(0.14986)	(0.00891)
City fixed effects	YES	YES	YES	YES	YES
Time fixed effects	YES	YES	YES	YES	YES
Observations	2619	2659	2450	2424	2393
R-squared	0.76587	0.93153	0.96373	0.91648	0.89014

Standard errors are in parentheses.
***p<0.01,**p<0.05,*p<0.1.

The results presented in Table 6 indicate that the estimated coefficients of the talent introduction policy variable are significantly positive at the 5% level across all secondary indicators. This evidence suggests that talent introduction policies not only increase the number of high-tech research and development (R&D) personnel and institutions but also improve other subdimensions of new-quality productivity, thereby reinforcing the robustness and credibility of the findings.

4.3.2 Substituting the Dependent Variable

Given the ongoing debate over the construction of a new-quality productivity index, this study adopts established measurement approaches from prior literature to provide an alternative quantification of new-quality productivity. The concept of new-quality productivity emphasizes its role as a key driver of industrial restructuring. Building on this premise, we draw upon the methodologies of Gan et al. (2011) and Zhang et al. (2024) and introduce the industrial structure upgrading index (AIS) and the industrial structure rationalization index (TL) as proxy variables.

$$AIS = \sum_{n=1}^{3}(P_n \times n)$$

$$TL = \sum_{i=1}^{n}\left(\frac{Y_i}{Y}\right) ln\left(\frac{Y_i}{L_i} / \frac{Y}{L}\right)$$

Specifically, AIS captures the degree of industrial structure upgrading, with P_n representing input into the n-th industry. A higher AIS value implies that the economy is shifting toward a more service-oriented structure, signalling industrial advancement. TL measures the rationalization of the industrial structure, where Y denotes output, L denotes employment, i indexes industries, and n represents the total number of industrial sectors. A higher TL value indicates greater deviation from equilibrium, suggesting a less rational industrial structure.

Table 7: Robustness Check with Alternative Dependent Variables

	TL Industrial Structure Rationalization	AIS Industrial Structure Upgrading Index

Talent introduction policy	-0.02556**	0.04865***
	(0.01091)	(0.01572)
GDP growth rate	-0.12406	0.26501
	(0.1225)	(0.1897)
Proportion of added value of the secondary industry	-0.11739	-3.90638***
	(0.08461)	(0.18186)
Unemployment rate	-0.18542	-0.974
	(1.25639)	(1.88257)
Fixed-asset investment scale	-0.03184**	-0.02289
	(0.0144)	(0.02647)
Local government expenditure scale	0.12336	1.02952***
	(0.09072)	(0.32309)
Local government education expenditure scale	1.76548**	-2.32608
	(0.83473)	(1.41506)
Population density	-0.34255	0.71229
	(1.07782)	(2.06302)
Loan-to-deposit ratio	-0.12949*	0.1386
	(0.07076)	(0.08427)
Proportion of enrolled higher-education students	0.42077	-0.50511
	(0.33666)	(1.05163)
_cons	0.36997***	2.62383***
	(0.07773)	(0.14563)
City fixed effects	YES	YES
Time fixed effects	YES	YES
Observations	2372	3195
R-squared	0.80324	0.9358

Standard errors are in parentheses
***p<0.01,**p<0.05,*p<0.1

The regression results presented in Table 7 reveal that the talent introduction policy significantly improved both industrial structure upgrading and rationalization. These findings demonstrate that the policy effectively enhances regional new-quality productivity, thereby reinforcing the robustness of the empirical conclusions.

4.3.3 PSM—DID

This section further employs the propensity score matching–difference-in-differences (PSM-DID) approach to conduct a robustness check on the impact of the talent introduction policy on regional new-quality productivity. The results are presented in Table 8.

Table 8: PSM-DID Robustness Test

	(1)	(2)	(3)	(4)	(5)
	New-quality Productivity	New-quality Productivity	New-quality Productivity	New-quality Productivity	New-quality Productivity
Talent introduction policy	0.00097**	0.00093**	0.00087**	0.00087**	0.00088**
	(0.00041)	(0.00039)	(0.00037)	(0.00037)	(0.00036)
GDP growth rate		0.00506	0.00338	0.00338	0.00362
		(0.00385)	(0.00342)	(0.00341)	(0.00346)
Proportion of added value of the secondary industry		0.00025	0.00015	-0.00021	-0.00111
		(0.00149)	(0.00149)	(0.00181)	(0.00204)
Unemployment rate			-0.08688**	-0.08716**	-0.07623**
			(0.03874)	(0.03892)	(0.03824)
Fixed-asset investment scale			-0.00146**	-0.00146**	-0.00158***
			(0.00057)	(0.00058)	(0.0006)
Local government expenditure scale				-0.00105	-0.00096
				(0.0016)	(0.00159)

Local government education expenditure scale				-0.00201	-0.0083
				(0.0163)	(0.01697)
Population density					0.07746
					(0.06099)
Loan-to-deposit ratio					0.00011
					(0.00107)
Proportion of enrolled higher-education students					-0.00903
					(0.0072)
_cons	0.00468***	0.00412***	0.00609***	0.00651***	0.0038
	(0.0002)	(0.00058)	(0.00078)	(0.00123)	(0.0029)
City fixed effects	YES	YES	YES	YES	YES
Time fixed effects	YES	YES	YES	YES	YES
Observations	1512	1512	1512	1512	1512
R-squared	0.98168	0.98174	0.98242	0.98243	0.98273

Standard errors are in parentheses
*** p<0.01, ** p<0.05, * p<0.1

As shown, across all model specifications (Columns 1–5), the estimated coefficients of the talent introduction policy are positive and statistically significant at the 1% level. This indicates that the implementation of the talent introduction policy has led to a significant improvement in regional new-quality productivity. Specifically, the estimated coefficients range from 0.00087--0.00097, suggesting a consistently robust positive effect.

5. Further Analysis

5.1 Heterogeneity Analysis

Examining heterogeneity is of substantial theoretical and practical importance when exploring the role of human capital accumulation in enhancing regional new-quality productivity. Significant disparities in economic and social development exist across regions, and such differences may lead to varying policy effects of talent introduction initiatives. Heterogeneity analysis allows for a deeper understanding of the key factors that shape policy effectiveness, thereby providing a more comprehensive and accurate interpretation of the complex relationship between human capital accumulation and regional innovation-driven development.

Building on this perspective, this study adopts three heterogeneity groupings to investigate the effects of human capital accumulation on new-quality productivity from different angles. Specifically, the analysis is conducted along three dimensions: (1) fiscal capacity, (2) the scale of higher education resources, and (3) the stage of urban development. These three grouping methods are as follows: (1) grouping by high versus low fiscal self-sufficiency ratio; (2) grouping by the scale of the number of universities in the city; and (3) grouping by urban tier.

5.1.1 Fiscal Self-sufficiency Ratio

The fiscal self-sufficiency ratio is a key indicator of local government fiscal capacity and economic strength, directly influencing the formulation and implementation of talent-related policies. Regions with a high fiscal self-sufficiency ratio typically possess greater fiscal resources, enabling them to offer more attractive incentives and comprehensive support measures for talent recruitment. In contrast, regions with lower fiscal self-sufficiency may face more severe financial constraints in implementing such policies.

The grouping procedure is as follows: the fiscal self-sufficiency ratio is calculated as the difference between a city's fiscal revenue and expenditure, divided by its fiscal revenue, averaged annually. Cities with values above the annual mean are classified into the high group, and those with values below the annual mean are classified into the low group.

Table 9: Heterogeneity Analysis by Fiscal Self-Sufficiency

	Group with low fiscal self-sufficiency rate	Group with high fiscal self-sufficiency rate
	New-quality Productivity	New-quality Productivity
Talent introduction policy	0.00055**	0.00104***
	(0.00027)	(0.00028)
GDP growth rate	0.00244	0.0039**
	(0.0021)	(0.00186)
Proportion of added value of the secondary industry	-0.00355	-0.00441*
	(0.00254)	(0.00231)
Unemployment rate	-0.04206	-0.04211
	(0.03194)	(0.04081)
Fixed-asset investment scale	-0.00133**	-0.00103**
	(0.00056)	(0.00041)
Local government expenditure scale	-0.0015	-0.00922**
	(0.00111)	(0.00376)
Local government education expenditure scale	0.00086	0.01745
	(0.01859)	(0.01706)
Population density	0.10147**	0.03692
	(0.03965)	(0.03562)
Loan-to-deposit ratio	-0.00062	-0.00165
	(0.00085)	(0.00118)
Proportion of enrolled higher-education students	0.00154	-0.00405
	(0.0106)	(0.00738)
_cons	0.00385	0.00802***
	(0.0026)	(0.00226)
City fixed effects	YES	YES
Time fixed effects	YES	YES
Observations	1782	1676
R-squared	0.99232	0.98749

Standard errors are in parentheses
***p<0.01,**p<0.05,*p<0.1

As shown in Table 9, the impact of the talent introduction policy on new-quality productivity is stronger in cities with high fiscal self-sufficiency than in those with low self-sufficiency. This suggests that stronger fiscal capacity enables cities to offer more competitive and attractive supporting measures for talent recruitment, thereby attracting a larger inflow of skilled workers and driving greater improvements in new-quality productivity.

5.1.2 Talent Pool

Universities serve as vital hubs for knowledge creation and talent cultivation, and their scale and number directly influence a region's talent supply and capacity for innovation. Cities with more education institutions typically enjoy richer educational resources and a more vibrant academic environment. This not only facilitates the attraction and development of highly skilled professionals but also fosters university–industry–research collaborations, accelerating knowledge transfer and technological innovation.

To examine the moderating role of university scale—an important regional characteristic—in the relationship between human capital accumulation and the advancement of new quality productive forces, we group cities on the basis of the number of universities they host. Specifically, we calculate the annual mean number of universities across all cities: those above the mean are classified into the "high" group, and those below the mean are classified into the "low" group. Given China's uneven distribution of educational resources, the majority of cities fall into the low group, reflecting the scarcity of university resources in many regions and resulting in a sample imbalance.

Table 10: Heterogeneity Analysis by Talent Pool Size

	Low group	High group
	New-quality Productivity	New-quality Productivity
Talent introduction policy	0.00045***	0.00111*
	(0.00016)	(0.00058)
GDP growth rate	0.00215	0.0058*
	(0.0016)	(0.00329)
Proportion of added value of the secondary industry	-0.00063	0.00361
	(0.00108)	(0.00274)
Unemployment rate	-0.03475	0.01847
	(0.02208)	(0.03266)
Fixed-asset investment scale	-0.001***	-0.00116
	(0.0003)	(0.00086)
Local government expenditure scale	-0.00293**	-0.00213
	(0.00128)	(0.00202)
Local government education expenditure scale	0.00537	-0.00193
	(0.01106)	(0.02426)
Population density	0.12582*	0.01152
	(0.06728)	(0.02089)
Loan-to-deposit ratio	-0.00009	-0.00187
	(0.00058)	(0.00172)
Proportion of enrolled higher-education students	0.0002	-0.00056
	(0.00611)	(0.00939)
_cons	0.00016	0.00832***
	(0.00261)	(0.00267)
City fixed effects	YES	YES
Time fixed effects	YES	YES
Observations	2645	665
R-squared	0.98636	0.99502

Standard errors are in parentheses
***p<0.01, **p<0.05,*p<0.1

As shown in Table 10, cities in the high-university group experience a stronger positive effect of talent introduction policies on the enhancement of new quality productive forces. This finding supports the view that cities with more universities typically possess richer educational resources and more dynamic academic environments, which are conducive to attracting and nurturing high-caliber talent. This finding also suggests that students pursuing higher education locally are substantially likely to remain in the same city for their professional development.

5.1.3 Urban classification

Cities at different tiers exhibit pronounced disparities in economic development, industrial structure, innovation environment, and talent attractiveness. These differences may cause the impact of human capital accumulation on new quality productive forces to vary in both pattern and magnitude. Grouping cities by tier enables a systematic examination of how this composite factor moderates the effectiveness of talent introduction policies, offering insights into the intrinsic relationship between a city's stage of development and its capacity for innovation. Moreover, such analysis provides valuable guidance for formulating differentiated talent policies aligned with the realities of each city's development stage. Following the *China City New Tier Classification List (2022 Edition)*, cities are categorized as "new first-tier," "first-tier," "second-tier," "third-tier," "fourth-tier," or "fifth-tier."

Table 11: Heterogeneity Analysis by Urban Hierarchy

	New First-tier	First-tier	Second-tier	Third-tier	Fourth-tier	Fifth-tier
	New-quality	New-quality	New-quality	New-quality	New-quality	New-quality

	Productivity	Productivity	Productivity	Productivity	Productivity	Productivity
Talent introduction policy	0.00777**	0.00349***	0.00031**	0.00024***	0.00016***	0.00044
	(0.00203)	(0.00116)	(0.00014)		(0.00005)	(0.00061)
GDP growth rate	0.05282	0.02526	-0.00342	0.00182	-0.00045	-0.00023
	(0.05653)	(0.01893)	(0.0087)	(0.00203)	(0.00051)	(0.00022)
Proportion of added value of the secondary industry	-0.08714	-0.01874*	0.00243	-0.00002	-0.00088	-0.00003
	(0.06965)	(0.00901)	(0.00769)	(0.00138)	(0.00069)	(0.0002)
Unemployment rate	-0.26826	-0.02318	-0.13387*	-0.01414	0.00698	-0.00195
	(0.32542)	(0.13222)	(0.06768)	(0.01743)	(0.00815)	(0.00324)
Fixed-asset investment scale	-0.01333	-0.01606*	-0.00244	-0.00023	-0.00032**	-0.00005
	(0.02522)	(0.00751)	(0.00155)	(0.00031)	(0.00015)	(0.00004)
Local government expenditure scale	-0.00277	-0.0082	-0.01276	-0.00167	-0.00054	-0.00024*
	(0.06453)	(0.02661)	(0.0094)	(0.00132)	(0.00054)	(0.00013)
Local government education expenditure scale	-0.16807	-0.18303	-0.03827	0.01544	0.00213	0.00451***
	(0.2014)	(0.20694)	(0.09423)	(0.00976)	(0.00383)	(0.00164)
Population density	-0.01436	0.12281*	-0.06284	0.03564	-0.01167	0.00519
	(0.02746)	(0.06125)	(0.06181)	(0.02813)	(0.01)	(0.01103)
Loan-to-deposit ratio	-0.0392	0.01139	-0.00572	-0.00004	-0.00035	-0.00015
	(0.02969)	(0.01359)	(0.0036)	(0.00059)	(0.00025)	(0.0001)
Proportion of enrolled higher-education students	0.20348	0.07473	-0.044	0.05098*	0.00353***	-0.00133
	(0.38954)	(0.06963)	(0.03321)	(0.02824)	(0.00131)	(0.00225)
_cons	0.11136	0.02524*	0.02605***	-0.00016	0.00228***	0.00037
	(0.05677)	(0.01419)	(0.00752)	(0.00175)	(0.00063)	(0.00029)
City fixed effects	YES	YES	YES	YES	YES	YES
Time fixed effects	YES	YES	YES	YES	YES	YES
Observations	52	195	377	897	1027	884
R-squared	0.99777	0.98916	0.94574	0.95048	0.93063	0.90982

Standard errors are in parentheses
***p<0.01,**p<0.05,*p<0.1

The regression results in Table 11 reveal that the positive impact of talent introduction policies on new quality productive forces is stronger in more developed cities, displaying a gradually diminishing trend across lower tiers. Notably, the effect is statistically insignificant for fifth-tier cities. This suggests that talent introduction policies in more developed cities are inherently more attractive, thereby exerting a greater influence on the enhancement of regional new quality productive forces.

5.2 Policy Intensity

Building on an earlier analysis that considered only whether a city had implemented a talent introduction policy, this study refines the approach by introducing a more granular scoring mechanism to capture policy intensity. This overcomes the limitations of a simple binary (0–1) indicator and provides a more accurate measure of the comprehensive strength of these policies. This refinement offers a more reliable empirical basis for examining how the intensity of talent introduction policies influences the level of new quality productive forces.

Specifically, a five-tier scoring system (1–5 points) was developed to quantify policy intensity: (1) Formulation of a basic policy framework—1 point is assigned to cities that have issued a general framework for talent introduction. (2) Housing support—2 points if housing subsidies or preferential housing purchase policies are offered in addition to the basic framework. (3) Educational support for children—3 points if the policy additionally addresses school enrollment for the children of incoming talent. (4) Research funding support—4 points if start-up research funds or project grants are provided in addition to the above measures. (5) Comprehensive welfare and entrepreneurial support—5 points if the policy further includes benefits such as medical and pension insurance, entrepreneurial assistance, equity incentives, and other supplementary support.

Table 12: Extended Analysis of Policy Intensity

	(1)	(2)	(3)	(4)	(5)
	New-quality Productivity	New-quality Productivity	New-quality Productivity	New-quality Productivity	New-quality Productivity
Talent introduction intensity	0.00017***	0.00017***	0.00016***	0.00016***	0.00016***
	(0.00005)	(0.00005)	(0.00005)	(0.00005)	(0.00004)
GDP growth rate		0.00402*	0.00323	0.00324	0.0033
		(0.00237)	(0.0022)	(0.0022)	(0.00208)
Proportion of added value of the secondary industry		0.00097	0.0006	-0.00016	-0.00125
		(0.00093)	(0.00095)	(0.00125)	(0.00137)
Unemployment rate			-0.05325*	-0.05332*	-0.04371
			(0.03007)	(0.03019)	(0.02935)
Fixed-asset investment scale			-0.00119***	-0.0012***	-0.00124***
			(0.00035)	(0.00036)	(0.00036)
Local government expenditure scale				-0.00421***	-0.00376***
				(0.00152)	(0.00145)
Local government education expenditure scale				0.00819	0.00043
				(0.01244)	(0.01284)
Population density					0.08893**
					(0.03762)
Loan-to-deposit ratio					-0.00005
					(0.0008)
Proportion of enrolled higher-education students					-0.00187
					(0.00582)
_cons	0.0049***	0.0041***	0.00569***	0.00658***	0.00329*
	(0.00009)	(0.00042)	(0.00056)	(0.00102)	(0.00193)
City fixed effects	YES	YES	YES	YES	YES
Time fixed effects	YES	YES	YES	YES	YES
Observations	3458	3458	3458	3458	3458
R-squared	0.98438	0.98444	0.98493	0.985	0.98536

Standard errors are in parentheses
***p<0.01,**p<0.05,*p<0.1

The results in Table 12 indicate a clear positive relationship between policy intensity and the level of regional new quality productive forces. This suggests that talent introduction policies with more comprehensive supporting measures are more effective in attracting high-quality talent inflows, thereby driving the enhancement of new quality productive forces.

5.3 Policy Synergy

Building on the earlier analysis that incorporated technological innovation as a mediating variable, this study further extends the analytical framework to account for the dynamic interaction between human capital accumulation and technological innovation, as emphasized in the theoretical review. Following the approach of Zhou et al. (2024), we examine the joint effect of these two policy dimensions on regional new quality productive forces. Specifically, in line with Zhang et al. (2021), we employ the establishment of National High-Tech Industrial Development Zones as the policy variable for technological innovation.

Table 13: Extended Analysis of Policy Synergy

	(1)	(2)	(3)	(4)	(5)

	New-quality Productivity	New-quality Productivity	New-quality Productivity	New-quality Productivity	New-quality Productivity
Talent introduction policy × Technology innovation policy	0.00214***	0.00213***	0.00208***	0.00205***	0.00204***
	(0.00057)	(0.00057)	(0.00055)	(0.00055)	(0.00055)
GDP growth rate		0.00404*	0.00324	0.00326	0.00328
		(0.0023)	(0.00213)	(0.00214)	(0.00201)
Proportion of added value of the secondary industry		0.00055	0.00017	-0.00043	-0.00155
		(0.00096)	(0.00099)	(0.00127)	(0.00136)
Unemployment rate			-0.05568*	-0.05555*	-0.04604
			(0.02932)	(0.02946)	(0.02845)
Fixed-asset investment scale			-0.00116***	-0.00118***	-0.00121***
			(0.00033)	(0.00035)	(0.00034)
Local government expenditure scale				-0.0035**	-0.00301**
				(0.00142)	(0.00133)
Local government education expenditure scale				0.00722	-0.00069
				(0.01185)	(0.01224)
Population density					0.09094**
					(0.0367)
Loan-to-deposit ratio					-0.00015
					(0.00079)
Proportion of enrolled higher-education students					-0.00135
					(0.00588)
_cons	0.00518***	0.00458***	0.00612***	0.00684***	0.00349*
	(0.00008)	(0.00043)	(0.00063)	(0.00106)	(0.00191)
City fixed effects	YES	YES	YES	YES	YES
Time fixed effects	YES	YES	YES	YES	YES
Observations	3458	3458	3458	3458	3458
R-squared	0.98503	0.98508	0.98556	0.98561	0.98597

Standard errors are in parentheses
***p<0.01,**p<0.05,*p<0.1

The results presented in Table 13 reveal that the interaction term between talent introduction policies and technological innovation policies—representing policy synergy—has a more pronounced positive effect on new quality productive forces than does either policy alone. This finding suggests that the combined force of human capital accumulation and technological innovation policies is more conducive to enhancing regional new quality productive forces.

6. Conclusions and Policy Implications

Using city-level panel data from 2010--2022, this study empirically examines the impact of human capital accumulation and technological innovation on regional new quality productive forces, yielding the following key findings: (1) Human capital accumulation significantly enhances regional new quality productive forces. Leveraging municipal talent introduction policies as an exogenous shock to human capital accumulation, we find that, even after controlling for a variety of covariates, the coefficient of the talent introduction policy variable remains significantly positive at the 1% level. This finding indicates that measures such as talent introduction, which attract and retain high-quality human capital, can substantially increase regional new quality productive forces. (2) Human capital accumulation operates through technological innovation to drive new quality productive forces. The analysis confirms the proposed mechanism—human capital accumulation fosters regional technological innovation, which in turn increases the level of new quality productive forces. (3) Robustness checks support the validity of the results. Parallel trend tests, placebo tests, subindicator regressions, replacement of the dependent variable, and PSM–DID estimations all affirm the stability of the core findings. (4) Further analyses reveal heterogeneity in policy effects. The positive effect of human capital accumulation is stronger in regions with higher fiscal self-sufficiency, greater talent scale, and more advanced urban tiers. Moreover, the more comprehensive the supporting measures accompanying talent introduction policies are, the greater their effectiveness.

Considering policy synergy, the joint implementation of human capital accumulation and technological innovation policies produces a more pronounced improvement in regional new quality productive forces. On the basis of these findings, this study proposes the following policy recommendations to further advance the development of new quality productive forces.

6.1 Strengthening Talent Introduction Policies with Comprehensive Support Measures

Our empirical findings underscore that human capital accumulation—particularly via targeted talent introduction policies—is a critical driver of regional new quality productive forces. To further enhance these effects, local governments should design precise, effective policies and ensure complementary support systems that create sustained agglomeration effects.

First, targeted talent introduction strategies should be formulated. Policies should be tailored to local industrial bases, development goals, and talent needs. Regions with strong industrial foundations and high talent demand should focus on attracting high-level and scarce talent, whereas those with weaker foundations should prioritize mid- to high-skilled professionals urgently needed for industrial upgrading. Policy sustainability is essential—regions should avoid indiscriminate or short-term “talent grabs.” Second, conducive work and living environments should be provided. While some regions offer generous incentives, inadequate supporting measures often lead to talent attrition. Authorities should address both professional and personal needs by providing comprehensive policy support and high-quality public services. Third, the potential of existing talent pools should be maximized. Local governments should leverage current talent as role models and facilitators, offering platforms for them to contribute through research, entrepreneurship, and intellectual property development. Simultaneously, policies should expand training opportunities for local residents, building a reserve of talent aligned with the demands of new quality productive forces.

6.2 Advancing Regional Technological Innovation

Technological innovation is the core driver of new quality productive forces, and this study confirms the catalytic role of human capital accumulation in fostering innovation. Building on this evidence, regions should strengthen their innovation-oriented thinking and design targeted policy measures to continuously increase their technological innovation capacity.

First, investment in scientific and technological research and development (R&D) should be increased. Sustained technological progress requires stable and substantial funding. Local governments should adjust fiscal expenditure structures to increase both the share and efficiency of science and technology spending. On the one hand, government investment in innovation should be prioritized in budget allocations, ensuring sustained growth in funding for science and technology projects. On the other hand, policies should guide and incentivize enterprises to expand their R&D expenditures—through tax incentives, venture capital funds, and other mechanisms—to provide robust financial support for corporate innovation. Second, industry–university–research (IUR) collaboration should be deepened. Such collaboration is a proven pathway for improving the transformation rate of scientific achievements. Governments should play a coordinating role by building effective cooperation platforms that encourage close partnerships between universities, research institutes, and enterprises. Policy support should be provided for joint research initiatives, personnel exchanges, and the commercialization of results. Firms should be encouraged to engage deeply with academic and research institutions in the early stages of R&D, fostering a synergistic innovation ecosystem. Third, intellectual property (IP) protection should be strengthened. Effective IP protection is a prerequisite for translating technological advances into practical applications. Legal frameworks should be continually improved, the enforcement capacity should be enhanced, and infringements should be strictly penalized to safeguard innovators’ rights. In parallel, IP management reforms should accelerate rights confirmation and market transactions, ensuring efficient utilization. A well-functioning IP protection system creates a secure and favourable environment for innovation activities. Fourth, regional innovation layouts should be optimized. Drawing on domestic and international best practices, regional innovation resources should be strategically allocated to form a coordinated and complementary network. Development should focus on high-tech industrial parks, technology business incubators, and other innovation hubs that attract talent and concentrate technological capacity. Moreover, each locality should leverage its unique geographical and resource advantages to develop specialized innovation systems, fostering distinctive clusters of technological excellence.

6.3 Improving Policy Evaluation and Dynamic Adjustment Mechanisms

The heterogeneity and extended analyses in this study demonstrate that policy effectiveness varies across regions and conditions. To ensure the sustained impact of talent introduction and technological innovation policies, local governments should establish comprehensive evaluation and feedback mechanisms, enabling timely and evidence-based policy adjustments.

First, we establish a systematic evaluation framework for talent introduction policies. Such policies should evolve in line with industrial development trends and labor market dynamics, maintaining both foresight and flexibility. A robust evaluation and feedback mechanism should be implemented to assess policy outcomes periodically, identify blind spots or shortcomings, and make timely adjustments to improve policy relevance and effectiveness. Second, maintain policy continuity. Talent introduction measures should not be sporadic or "blindly" implemented; rather, they must be sustained over time. New policies should build upon the foundations of earlier initiatives—retaining effective practices and promptly revising elements that underperform. Third, regular assessments of technological innovation policies should be implemented. Evaluation should cover the adequacy of policy design, the effectiveness of implementation, and the actual contribution to innovation capacity and new quality productive forces. This includes assessing areas such as R&D investment, industry–university–research collaboration, and innovation platform development. Fourth, policy synergy between talent introduction and technological innovation should be strengthened. Although these belong to distinct policy domains, their roles in advancing new quality productive forces are interdependent and mutually reinforcing. Coordination in policy formulation can ensure coherent objectives, complementary measures, and integrated implementation. Fifth, institutionalize dynamic adjustment mechanisms. Continuous policy evaluation should feed into a rolling revision process. Effective measures should be consolidated and scaled, while weaknesses should be addressed through targeted improvements. This will enhance both the precision of policy design and the efficiency of execution.

6.4 Addressing Challenges and Risks in Policy Implementation

The implementation of human capital accumulation and technological innovation policies may face multiple challenges that require careful consideration during both the formulation and execution stages.

First, there are dual pressures of talent attraction and retention. While some regions can successfully attract highly skilled professionals, high living costs, insufficient support services, or limited career development opportunities may lead to talent outflow, undermining long-term policy effectiveness. Second, competitive pressures arise from regional disparities. The siphoning effect of economically developed areas on high-end talent and innovation resources may exacerbate shortages in less developed regions, resulting in uneven improvements in new quality productive forces. The third factor is fiscal and resource constraints. Sustained and intensive funding is required for both scientific R&D and talent introduction. However, in regions facing significant fiscal pressures, securing long-term financial resources may prove challenging, thereby affecting policy continuity and effectiveness. Fourth, uncertainty and market risks in technological innovation. Innovation involves long cycles, substantial investment, and inherent risks of failure. If research outcomes cannot be effectively commercialized or gain sufficient market acceptance, the anticipated improvements in new quality productive forces may not materialize. The fifth factor is inadequate policy execution and coordination. Weak interdepartmental communication and insufficient coordination during policy implementation may lead to execution deviations or redundant projects, reducing overall policy efficiency.

To address these challenges, local governments should conduct ex ante risk assessments, prepare contingency plans, and adopt measures such as optimizing resource allocation, improving support services, and strengthening regional cooperation. These steps help minimize implementation risk and maximize the synergistic effects of human capital accumulation and technological innovation.

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