Published online: 18 November 2024 DOI: 10.54254/2977-5701/13/2024126

Analysis of the Impact of Talent Introduction Policies on Urban Development Based on a Multi-Period Difference-in-Differences Model: A Case Study of the Yangtze River Delta Urban Agglomeration

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Abstract. Since the beginning of the new century, the process of globalization has deepened, prompting local governments to implement talent introduction policies to maintain sustainable urban development. Focusing on 27 cities in the Yangtze River Delta region, this study collects talent introduction policy texts and panel data from 2000 to 2010. Using Latent Dirichlet Allocation (LDA) for topic mining on text data, five main topics are identified: talent structure, industrial development, scientific and technological expenditures, financial development level, and innovation and entrepreneurship. To investigate the impact of talent introduction policies on these five topics and the overall level of urban economic development, this study uses the "talent introduction policy" as a quasi-natural experiment. Empirical analysis is conducted with a multi-period difference-in-differences (DID) model and double machine learning to explore the intrinsic mechanisms by which these policies empower urban economic development. The results reveal that: (1) Talent introduction policies have significantly promoted urban economic development, and this conclusion remains robust after a series of tests; (2) These policies indirectly boost urban economic development by enhancing financial development efficiency and increasing educational expenditure; (3) The economic growth-promoting effects of talent introduction policies are more evident in provincial capitals or municipalities, eastern cities, and cities with "211 Project" universities; (4) Talent introduction policies positively impact scientific and technological expenditures and innovation and entrepreneurship, negatively impact industrial structure, and have no significant effect on talent structure and financial development level. This study confirms the necessity of talent introduction policies since the beginning of the new century and provides recommendations for their continued implementation.

Keywords: Talent Introduction Policy, multi-period difference-in-differences Model, LDA topic model, economic growth, double machine learning

1. Introduction

The 20th National Congress of the Communist Party of China highlighted that "education, science and technology, and talent are foundational and strategic supports for building a modern socialist country in all respects." With the deepening of globalization and the continuous development of high-tech industries, the demand for highly qualified talent in various sectors has increased significantly. As the primary resource, talent has become a focus for the central government, which has issued numerous talent introduction initiatives—such as the Overseas High-Level Talent Introduction Plan—understanding the new challenges of the 21st century and fostering a policy environment that attracts talent.

The term "talent" frequently appears in various government documents, and talent introduction has gradually become a priority for government work. Since 2000, local governments in cities like Nanjing and Shanghai have successively introduced various talent introduction policies. These policies primarily target high-level domestic and international talents, including highly educated and skilled professionals, top experts across industries, experienced business executives, and entrepreneurs. The main incentives in these talent policies include support for innovation and entrepreneurship, economic subsidies, and housing assistance. The Yangtze River Delta region, known for its rapid economic development and its role as a bellwether of domestic economic progress, saw cities within the region introduce talent introduction policies at the start of the century. This study thus focuses on the key question of how talent introduction policies since the beginning of the new century have impacted urban economic benefits and seeks to explore the underlying mechanisms at work.

Based on the above analysis, this paper takes talent introduction policies as a quasi-natural experiment. First, it collects talent introduction policies implemented by cities in the Yangtze River Delta region from 2000 to 2010. Using the Latent Dirichlet Allocation (LDA) model, the study generates a topic-word probability distribution, organizes the top ten high-probability feature words for each topic, determines the content of each topic based on these high-probability words, and identifies and labels the topics. Indicators are selected to describe each topic, which, along with the level of urban economic development as the dependent variable, are used to examine the impact of talent introduction policies on cities. Subsequently, based on selected control and mediating variables, a multi-period difference-in-differences (DID) model is constructed to further analyze the issue.

The contributions of this study are as follows: (1) Currently, the academic community has paid limited attention to evaluating the effectiveness of talent introduction policies using difference-in-differences models, with most studies focusing on the post-2010 period. This paper examines the impact of talent introduction policies on economic growth from the perspective of the Yangtze River Delta region since the beginning of the new century. By using a multi-period DID model, the policy variables are tailored to different cities, making the results more reasonable and reliable, thus providing a new perspective and reference for the quantitative evaluation of talent policies. (2) For talent policy evaluation, this paper introduces the LDA topic model, which processes collected policy texts to obtain the topic-word probability distribution. This provides a crucial reference for selecting dependent variables, enabling a more reasonable and accurate investigation of the impact of talent introduction policies on cities. This innovative combination of topic recognition models and econometric models enhances the experiment's credibility and rigor. (3) This study conducts an in-depth analysis of the mechanisms behind the promoting effect of talent introduction policies on urban economic development. The conclusions and insights drawn from this research can serve as a theoretical basis for policy review and analysis and provide valuable experience for the further implementation and optimization of talent policies in the future.

2. Literature Review

From the perspective of policy evaluation methods, commonly used approaches can be broadly divided into qualitative and quantitative evaluations. In qualitative evaluation, Zhong Ziyang focused on Changzhou City as a case study, employing public policy framework analysis and comparative analysis methods to examine issues in local government decision-making related to attracting high-level overseas talent [1]. Su Jinjin used literature review, comparative analysis, and inductive-deductive methods to study issues in Tianjin's high-level talent introduction policies, drawing insights from the successes and challenges faced by talent policies in Wuhan and Xi’an [2]. In terms of quantitative research, policy evaluation in academia primarily employs methods such as the Policy Modeling Consistency (PMC) Index model, principal component analysis, AHP-Entropy Method, difference-in-differences (DID) method, Data Envelopment Analysis (DEA), and text econometrics. These approaches integrate methodologies from econometrics, natural language processing, and other fields. For instance, Yang Heqing and Chen Yian constructed an evaluation index system for government talent attraction policies from three dimensions — “ability to attract, retain, and utilize talent”—using factor analysis to assess the implementation of the “Thousand Talents Program” and suggested future adjustments for the policy [3]. Chen Yuangang and Li Chu employed the DID method to conduct an empirical study on the mechanisms by which talent introduction policies impact economic growth, exploring whether employment scale and industrial structure act as mediators within the economic growth framework [4]. However, each of these evaluation methods has its strengths and limitations. This paper adopts a balanced approach by combining qualitative and quantitative research based on the issues and needs specific to the study, utilizing the strengths of each method. It also integrates both pre-evaluation of policy design and post-evaluation of policy effects for a comprehensive evaluation of policy outcomes. In terms of talent policy evaluation, there has been limited exploration in academia to date. This paper attempts to address this gap by integrating the Latent Dirichlet Allocation (LDA) topic model from the field of text mining with the multi-period DID model from econometrics. Through this approach, it explores the impact of talent policies on urban development, the efficacy of these policies in promoting urban economic growth, and the internal mechanisms at play, providing strategic recommendations for optimizing talent policies.

3. Policy Content Analysis

3.1. Sample Selection

The Yangtze River Delta (YRD) region is one of China’s most economically developed and highly urbanized areas, leading the nation in economic output, industrial structure, and technological innovation. As a forefront region of China's reform and opening-up, the YRD benefits from numerous policy advantages and institutional innovation opportunities. The local governments in this region have actively taken measures to promote economic transformation, upgrade the business environment, and support urban development, making the analysis of talent introduction policies in the YRD region relevant and insightful for similar policies across China.

Using the Peking University Law Database as a data source, this study retrieved all policies issued by the Yangtze River Delta urban agglomeration (a total of 27 cities, including Shanghai, Nanjing, etc.) between January 1, 2000, and December 31, 2010.

Policies were identified if their titles contained keywords such as "encourage," "overseas," "high-level," "introduction," "study abroad," or "elite," and their full text included the word "talent." To ensure a high degree of relevance to talent policies, all retrieved policy texts were manually reviewed, resulting in a final collection of 58 policy documents. The preamble sections of these documents were selected, saved in an Excel file, and used as the dataset for analysis.

3.2. Research Methods

This study uses the Latent Dirichlet Allocation (LDA) topic model for topic mining and analysis. The LDA model, first introduced by Blei et al. in 2003[5], is widely used in text mining, information retrieval, and natural language processing. LDA assumes that each document is a mixture of multiple topics, and each topic is composed of several words with a specific probability distribution. The objective of the LDA model is to estimate these distributions from observed document-word data and to uncover the latent thematic structure within a collection of documents. To determine the optimal number of topics, this study uses perplexity as a metric. A visualization model is also constructed to assist with analysis. Using the bag-of-words model, this study employs the CountVectorizer function from Python's Sklearn library to vectorize word frequencies, and the Latent Dirichlet Allocation function for LDA topic modeling. This process generates the "topic-word" probability distribution for the optimal topics, which is then visualized with the pyLDAvis library.

3.3. Construction of the Topic Mining Model

3.3.1. Text Preprocessing

A total of 58 effective talent policy documents were compiled, including 24 from Jiangsu Province, 6 from Shanghai, 25 from Zhejiang Province, and 4 from Anhui Province. Text segmentation was performed using Python's Jieba library. To refine the data, stop words specific to policy characteristics were removed, using custom stop word lists from sources such as HIT, Baidu, CN, and SCU.

3.3.2. LDA Data and Analysis

The preprocessed data was input into the LDA model for calculation, yielding perplexity values. As shown in Figure 1, perplexity is lowest when the number of topics is set to 5 and 7. Visualization of the LDA topic model was conducted using the pyLDAvis library. In Figure 1, when the topic number is set to 5, the topic boundaries are clear and well-categorized. However, at 7 topics, there is considerable overlap among Topics 3, 4, and 5, resulting in poorer classification. Therefore, the optimal number of topics was determined to be 5.

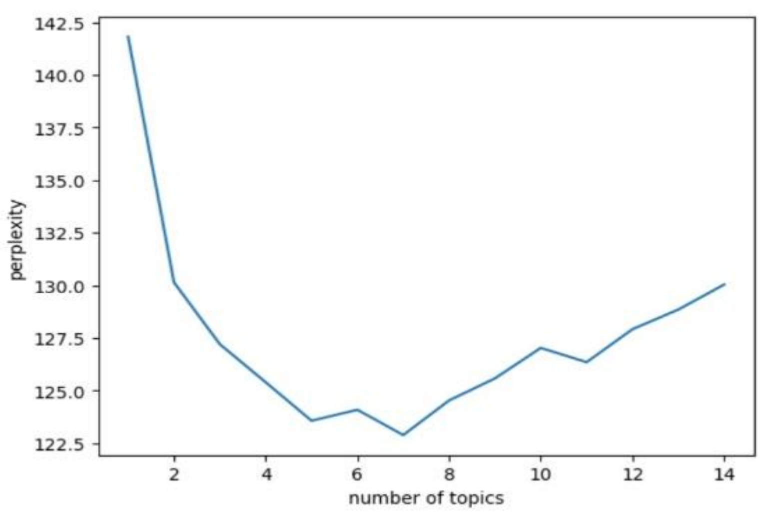

Figure 1. number of topics

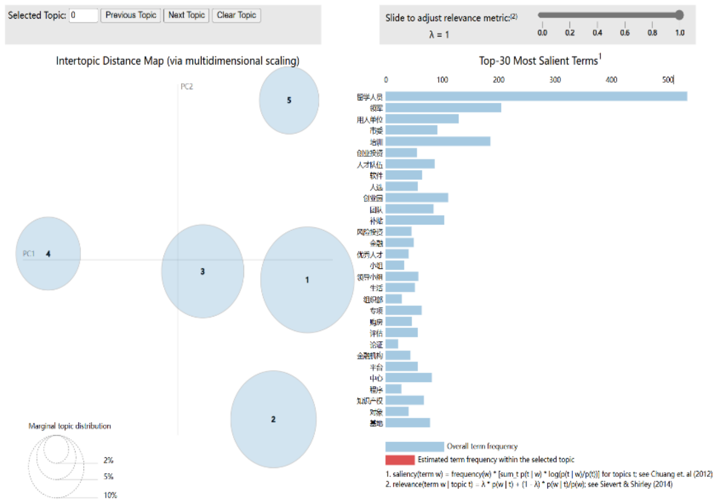

Figure 2. “topic-word”

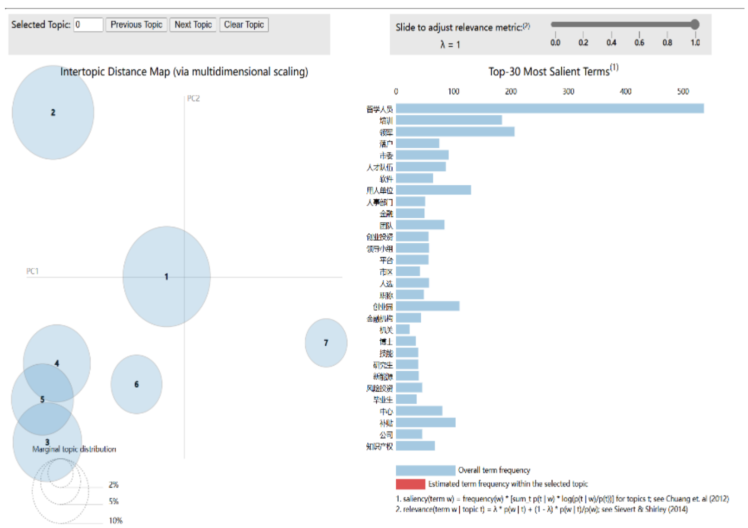

Figure 3. “document-topic”

Once the LDA topic model was trained, the "topic-word" and "document-topic" probability distributions were extracted. For the "topic-word" distribution, the top 11 high-probability feature words for each topic were organized. Based on these high-probability feature words under each topic, the topic contents were identified, labeled, and categorized into five major themes, as shown in Table 1.

Table 1: LDA Topic-Word Distribution

Number	Topic	Keywords
Topic0	Talent Structure	Training, Talent Pool, Education, Management, Intelligence, Mechanism, Position, System, Activity, Technical Staff, Skills
Topic1	Industrial Development	Overseas Personnel, Entrepreneurship Park, Technological Achievements, Expenses, Employers, Consultation, Special Funds, Patents, Park, Contribution, Development Zone
Topic2	Technological Expenditure	Employers, Municipal Committee, Candidates, Team, Leadership Group, Outstanding Talent, Living, Housing, Subsidy, Organization Department, Procedure
Topic3	Financial Development Level	Subsidy, Software, Base, Finance, Center, Platform, Settlement, Training, Intellectual Property, Financial Institutions, Loan
Topic4	Innovation and Entrepreneurship	Leading, Venture Capital, Risk Investment, Evaluation, Group, Special Projects, Product, Production, Verification, Rent, Intellectual Property

4. Research Design

4.1. Mechanism and Research Hypotheses

In the mid-1980s, in response to the inability of Solow's neoclassical growth theory to explain actual economic growth, scholars like Paul Romer and Robert Lucas proposed the "new growth theory" [18]. This theory introduced knowledge and specialized human capital into growth models, suggesting that the accumulation of knowledge and specialized human capital could yield increasing returns, thereby enhancing the returns of other input factors and leading to overall increasing returns to scale. This demonstrates that the continuous and permanent source of economic growth lies in these factors. Therefore, talent policies that introduce high-level talent can effectively drive sustained economic growth. Based on this, we propose the following research hypothesis:

Hypothesis 1: Talent introduction policies have a positive effect on urban economic growth.

While talent introduction policies directly stimulate urban economic growth, they can also indirectly empower urban growth by enhancing financial development efficiency and educational expenditure.

From the keywords identified in the policy text analysis in Table 1, it can be seen that talent introduction policies mention "venture capital," "risk investment," etc. Additionally, many policies documents mention attracting "young and middle-aged senior engineering and management talent who have worked in foreign financial institutions, large enterprises, and international organizations in fields such as finance, engineering technology, and management." This indicates that talent introduction policies encourage entrepreneurship by attracting senior financial and management talent, thereby promoting the development of the financial sector and enterprises in cities. Given the high-risk, high-investment, and long-cycle characteristics of innovation and entrepreneurship, talent introduction policies use flexible policies and financial support to establish mechanisms that connect enterprises with financial institutions. Moreover, by introducing financial talent to optimize the financial system, these policies continuously improve financial development efficiency, thereby driving the growth of urban financial sectors and various emerging enterprises. Based on this, we propose the following research hypothesis:

Hypothesis 2: Talent introduction promotes economic growth by enhancing financial development efficiency.

Talent introduction policy documents also mention that introduced talent will enjoy various subsidies. Therefore, in the processes of building talent teams in universities and advancing innovation projects, funding for science, technology, and education will increase. Some scholars have pointed out a significant correlation between educational investment, particularly in higher education, and economic growth [6]. Increased educational expenditure optimizes educational facilities, improves teacher salaries, and enhances education quality, benefiting students and effectively nurturing the city's talent reserves, thus injecting new vitality into the city's future development. Based on this, we propose the following research hypothesis:

Hypothesis 3: Talent introduction promotes economic growth by increasing government education expenditure.

Additionally, this study employs the LDA model to analyze the content of policy texts, enabling precise and effective identification of the specific aspects that talent introduction policies focus on. According to the topic-word results derived from the model, we can investigate the specific efficacy of talent introduction policies on urban development by examining whether they impact the areas of talent structure, industrial development, government investment, financial development level, and entrepreneurship support. Based on this, this paper will also investigate the impact of talent introduction policies on urban development from these five targeted aspects.

4.2. Model Construction and Data Selection

4.2.1. Model Construction

This study considers the implementation of talent introduction policies by cities as a quasi-natural experiment, constructing the following multi-period DID model:

$$AGDP_{i,t} = \alpha_0 + \alpha_1 DID_{i,t} + \alpha_2 X_{i,t} + \mu_i + \lambda_t + \varepsilon_{i,t} \tag{1}$$

$$DID_{i,t} = T_{i,t} \times P_{i,t} \tag{2}$$

Where i and t represent the city and year, respectively; $AGDP_{i,t}$ denotes the per capita GDP of city iii in period t, which reflects the level of regional economic development and is the dependent variable. $DID_{i,t}$ is the core explanatory variable of this study, a dummy variable for the talent introduction policy. If city i implemented this policy in year t, then $DID_{i,t}$ takes the value of 1; otherwise, it is 0. $X_{i,t}$ represents other characteristic variables that may influence the regional economic development level in city iii at year t, including the level of urban industrialization, fixed asset investment, degree of government intervention, financial development level, and urban talent cultivation. μ_i denotes the regional fixed effect; λ_t represents the time fixed effect; $\varepsilon_{i,t}$ is the random disturbance term; and α_0 is the constant term. The most crucial coefficient in this study, α_1 represents the impact of talent introduction policies on the economic development level of urban areas.

In addition to constructing the multi-period DID model, a mediation effect model is needed to examine the mechanisms.

$$M_{i,t} = \beta_1 + \beta_2 DID_{i,t} + \beta_3 X_{i,t} + \varepsilon_{i,t} \tag{3}$$

$$AGDP_{i,t} = \beta_4 + \beta_5 DID_{i,t} + \beta_6 M_{i,t} + \beta_7 X_{i,t} + \varepsilon_{i,t} \tag{4}$$

Where $M_{i,t}$ represents the mediating variable, including education expenditure and financial development efficiency, represented by lnecost and tds respectively. According to the mediation effect models (3) and (4), we conduct stepwise testing. If β_2, β_5 and β_6 are all significant, this indicates a potential mediation effect. Additionally, this study incorporates a bootstrap test to increase the statistical reliability of the results.

4.2.2. Variable Settings and Description

(1) Dependent Variable: The dependent variable is regional economic development level (agdp), typically measured by per capita GDP to assess the economic development of a region. Among the five topics extracted by the LDA topic model: Topic0 (Talent Structure): Represented by the city's talent structure (lnlabor32), which is calculated as the logarithm of the ratio between the number of employees in the tertiary sector and the secondary sector [14]. Topic1 (Industrial Development): Represented by the degree of industrial advancement (ais1) [15]. Topic2 (Technological Expenditure): Represented by the logarithm of government expenditure on science and technology (lnscost). Topic3 (Financial Development Level): Represented by the financial development degree (finance), which is the ratio of financial institutions' deposits and loans to regional GDP. Topic4 (Innovation and Entrepreneurship): Represented by the total fixed asset investment (fixinv).

(2) Explanatory Variable: The explanatory variable is the talent introduction policy (did), with cities implementing talent introduction policies between 2000 and 2010 as the treatment group, and cities not implementing these policies as the control group. This yields 20 cities in the treatment group and 7 in the control group. The talent introduction policy variable (did) is an interaction term between policy implementation time and region. Specifically, if city i is within the implementation area, the regional dummy variable takes a value of 1; otherwise, it is 0. If period t is after policy implementation, the time dummy variable is 1; otherwise, it is 0.

(3) Mediating Variables: Based on the previous theoretical analysis, we select education expenditure as the mediating variable, represented by the logarithm of the education expense (lnecost) within fiscal expenditure. For the financial development efficiency (tds) indicator, we follow the approach of previous scholars [13], using the ratio of the total city loans and deposits to the total savings of urban and rural residents.

(4) Control Variables: Population Size (lnpopu): Represented by the logarithm of the city's registered population at the end of the year. Industrial Advancement (lnind): Represented by the logarithm of the ratio of the added value of the tertiary sector to the secondary sector in the same year. Degree of Openness (lnopen): Represented by the logarithm of the ratio of the total import and export volume to regional GDP. Consumption Level (lncost): Represented by the logarithm of the ratio of total retail sales of social consumer goods to regional GDP. Urbanization Rate (lnurban): Represented by the logarithm of the ratio of the non-agricultural resident population to the total resident population. Urban Talent Stock Level (lnaedu): Represented by the logarithm of the ratio of the number of enrolled students in regular higher education institutions to the city's registered population at year-end. Degree of Government Intervention (lngov): Represented by the logarithm of the ratio of the city government's budgeted expenditure to the city's GDP.

4.2.3. Data Description and Descriptive Statistics

This study uses panel data from 27 cities, including the Yangtze River Delta urban agglomeration and Wenzhou, from 2000 to 2010, to assess the impact of talent introduction policies on urban economic development levels. The primary data sources are the EPSDATA database, the Wind database, statistical yearbooks, and annual reports from various city statistical bureaus. Missing data were filled in using regression imputation. Descriptive statistics of the relevant variables are provided in the appendix.

4.3. Empirical Results and Analysis

4.3.1. Baseline Regression Analysis

Before analyzing the empirical results, the dependent, mediating, and control variables were standardized. To ensure the reliability of the experimental results, multicollinearity of the control variables was examined. The test results, provided in the appendix, show that the highest variance inflation factor (VIF) among the selected variables is 2.83, and the average VIF is 2.06, both within acceptable limits. This indicates that the econometric model does not suffer from severe multicollinearity. Based on this, the multi-period DID model is applied to estimate the effect of talent introduction policies on urban economic development levels.

Table 2. Baseline Regression Results

VARIABLES	(1) z_agdp	(2) z_agdp	(3) z_agdp	(4) z_agdp
did	0.319**	0.315**	0.306***	0.251***
	(0.132)	(0.117)	(0.107)	(0.0815)
z_lnpopu		8.464***	0.0350	3.909*
		(2.277)	(0.104)	(2.216)
z_lnind1		0.00161	0.0700	-0.0448
		(0.0834)	(0.0584)	(0.0657)
z_lnopen		-0.0831	0.300***	0.206
		(0.233)	(0.0972)	(0.187)
z_lncost		-0.0118	-0.103*	-0.0308
		(0.125)	(0.0580)	(0.0828)
z_lnurban		0.174*	-0.0401	-0.202**
		(0.0959)	(0.0864)	(0.0908)
z_lnaedu		0.544***	0.104	-0.130
		(0.181)	(0.0768)	(0.163)
z_lngov		-0.0281	-0.304***	-0.346**
		(0.105)	(0.110)	(0.125)
Constant	-0.778***	-0.162***	-0.853***	-1.109***
	(0.0741)	(0.0525)	(0.155)	(0.172)
Observations	297	295	295	295
R-squared	0.806	0.750	0.824	0.858
Number of id	27	27	27	27
controls	NO	YES	YES	YES
yearfix	YES	NO	YES	YES
idfix	YES	YES	NO	YES

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

As shown in Table 2, the baseline regression results reveal that talent introduction policies have a significant positive impact on urban economic development, regardless of whether control variables, time fixed effects, or individual fixed effects are included. Column (4) of Table 2 presents the regression results with control variables and both time and individual fixed effects. Here, the coefficient of the talent introduction policy on urban economic development is 0.251, significant at the 1% level, indicating that talent introduction policies do indeed enhance urban economic development, thereby supporting Hypothesis 1.

4.3.1.1. Parallel Trend Test

Meeting the parallel trend assumption is an important condition for using the multi-period DID model to evaluate policy effects. This test ensures that the treatment group and the control group follow a parallel trend before policy implementation, thereby satisfying the prerequisites for DID. For this study, we set a time interval of five years before and five years after the policy implementation, with the year before the policy implementation as the baseline.As shown in Figure 2, the coefficients for the four periods prior to the pilot policy implementation are below zero, with confidence intervals overlapping with zero, indicating that the treatment and control groups satisfy the parallel trend assumption before the policy implementation. As the talent introduction policy is implemented, the regression coefficients become positive and gradually increase, suggesting that the policy has had an increasingly positive impact on urban benefits. Therefore, the study meets the assumptions required for the multi-period DID analysis.

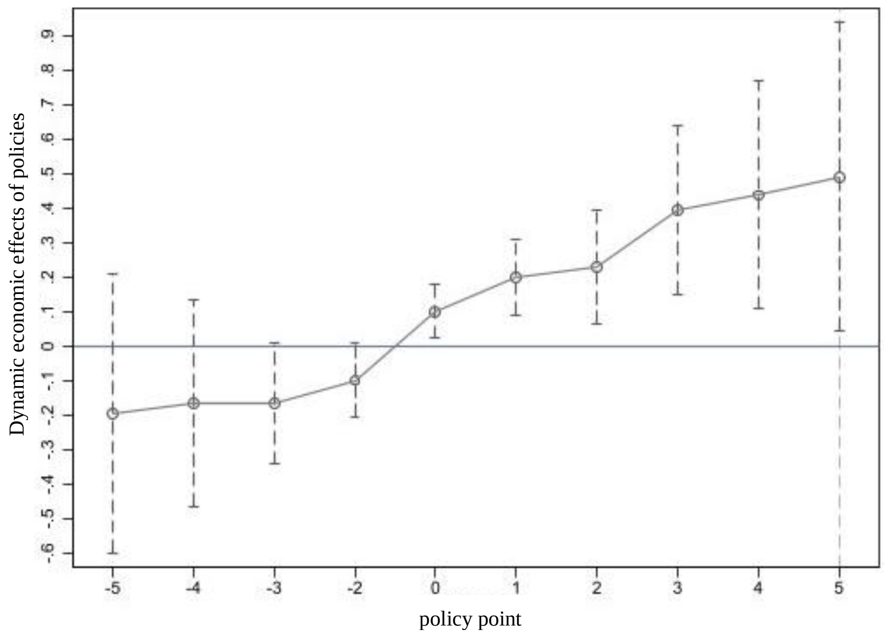

Figure 4. Policy Point and Dynamic Economic Effects of Policies

4.3.1.2. Robustness Test

(1) PSM-DID Test

To reduce selection bias and obtain a more comparable control group, this study uses the Propensity Score Matching Difference-in-Differences (PSM-DID) approach as a robustness check. Given the specific characteristics of the PSM and DID models, we treat the panel data as cross-sectional data for matching purposes. The study selects logged values of the following variables as covariates: registered population, industrial advancement, degree of openness, consumption level, urbanization rate, urban talent stock, and degree of government intervention. Using a Logit model, we calculate the propensity scores and perform nearest-neighbor matching within a caliper of 0.05, with a 1:2 ratio. To assess the matching effect, kernel density distribution plots are used. As shown in Figure 3, there is a substantial difference in propensity scores between the treatment and control groups before matching, but this difference is significantly reduced after matching, indicating a good matching effect. Figure 4 demonstrates that most samples fall within the common support area, satisfying the common support assumption.

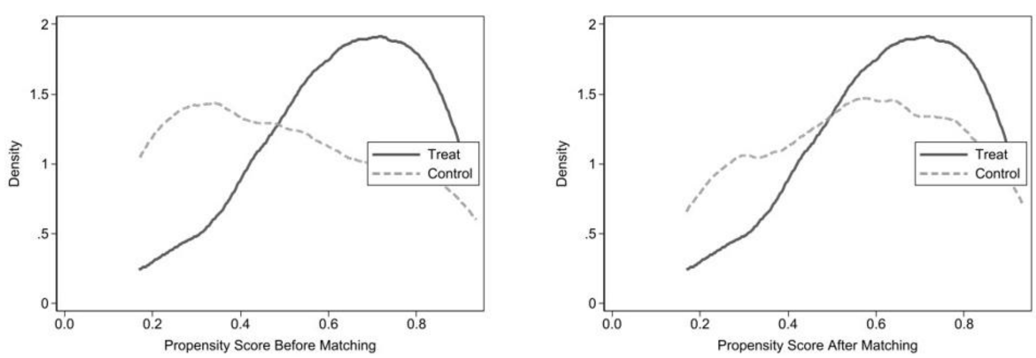

Figure 5. Propensity Score Before and After Matching with Density

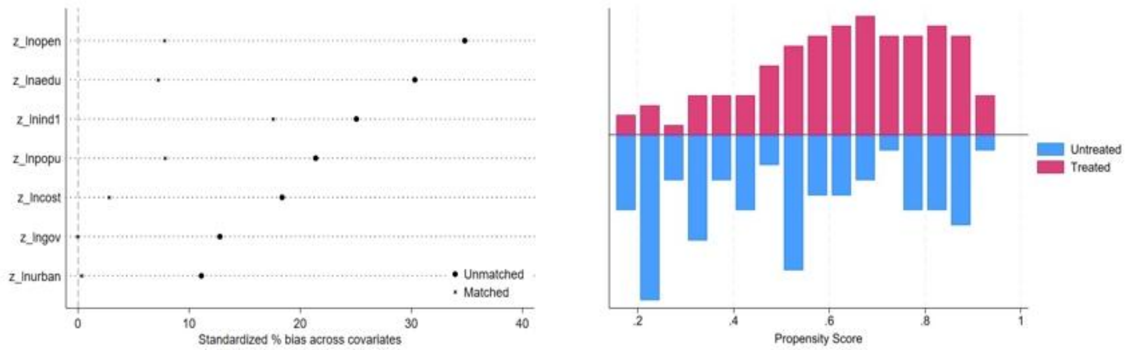

Figure 6. Standardized % bias across covariates and Propensity Score

In Column (5) of Table 2, the results from the PSM-DID model with both time and individual fixed effects are displayed. After accounting for city-specific differences, the impact of talent introduction policies on urban economic development remains significant, with a positive regression coefficient. This finding reinforces the policy's positive effect on urban economic growth, supporting Hypothesis 1.

(2) Double Machine Learning Model

The double machine learning approach combines traditional regression analysis with modern machine learning techniques, effectively avoiding issues related to the curse of dimensionality and multicollinearity. It also considers potential nonlinear relationships among variables, providing a more robust and unbiased estimate of causal effects and reducing the risk of model misspecification [11]. In this study, the sample is split into a 1:3 ratio, and Random Forest, Lasso Regression, and Gradient Boosting algorithms are used for estimation. As shown in Table 3, the regression coefficients for the talent introduction policy on urban economic development are consistently significant and positive across all models. These results are similar to those obtained from the difference-in-differences model, further supporting the positive impact of talent introduction policies on urban economic development, which validates Hypothesis 1.

Table 3. Comparison of Estimation Results Using Random Forest, Lasso Regression, and Gradient Boosting Algorithms

Algorithm	Random Forest		Lasso Regression		Gradient Boosting	
VARIABLES	z_agdp	z_agdp	z_agdp	z_agdp	z_agdp	z_agdp
did	0.256***	0.255***	0.283***	0.136***	0.171**	0.208***
	(0.0736)	(0.0729)	(0.0595)	(0.0422)	(0.0735)	(0.0760)
Constant	0.0111	0.0169	-0.0116	-0.0121	0.000525	-0.00566
	(0.0220)	(0.0226)	(0.0187)	(0.0150)	(0.0200)	(0.0203)
Control Variables (Linear Terms)	YES	YES	YES	YES	YES	YES
Control Variables (Quadratic Terms)	NO	YES	NO	YES	NO	YES
Time Fixed	YES	YES	YES	YES	YES	YES
Individual Fixed	YES	YES	YES	YES	YES	YES
Observations	295	295	295	295	295	295

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

4.3.2. Mediation Effect Analysis

Previous analyses have shown a close relationship between talent introduction policies and urban economic development. To further explore how these policies impact urban economic growth, this section examines two potential mediation channels identified earlier: rationalization of industrial structure and educational expenditure.

4.3.2.1. Mediation Effect of Financial Development Efficiency

As shown in Table 5, Columns (1), (2), and (3) present the results of the mediation effect test for financial development efficiency. Column (1) shows the baseline regression results of the policy variable on urban economic development. Column (2) shows the regression results of the policy variable on the mediating variable, financial development efficiency. The results indicate a positive coefficient for the talent introduction policy, significant at the 5% level, suggesting a positive impact of the policy on financial development efficiency. In Column (3), when the mediating variable (financial development efficiency) is included in the baseline regression model, the results show that financial development efficiency has a positive impact on urban economic development, significant at the 5% level. Additionally, the regression coefficient of the policy variable decreases and remains significant at the 5% level, indicating a partial mediation effect of financial development efficiency, which accounts for 39.4% of the total effect. Furthermore, Table 6 presents the results of a bootstrap test for financial development efficiency, with the indirect effect significant at the 1% level. These findings confirm that talent introduction policies positively affect financial development efficiency, thereby promoting urban economic growth, supporting Hypothesis 2.

4.3.2.2. Mediation Effect of Educational Expenditure

As shown in Table 5, Columns (4), (5), and (6) present the results of the mediation effect test for educational expenditure. Column (4) displays the baseline regression results of the policy variable on urban economic development. Column (5) shows the regression results of the policy variable on the mediating variable, educational expenditure. The positive coefficient of the talent introduction policy is significant at the 5% level, indicating a positive effect of the policy on educational expenditure. In Column (6), when educational expenditure is added to the baseline regression model, the results show that educational expenditure has a positive effect on urban economic development, significant at the 1% level. Additionally, the regression coefficient of the policy variable decreases and remains significant at the 5% level, indicating a partial mediation effect of educational expenditure, which accounts for 39.8% of the total effect. Table 6 further confirms this through a bootstrap test for educational expenditure, with the indirect effect significant at the 1% level. These results demonstrate that talent introduction policies positively impact educational expenditure, thereby promoting urban economic growth, validating Hypothesis 3.

Table 4. Mediation Effect Test

Mechanism Test	Rationalization of Industrial Structure Test			Educational Expenditure Level Test		
	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES	z_agdp	z_ais2	z_agdp	z_agdp	z_lnescost	z_agdp
did	0.251***	0.240**	0.152**	0.251***	0.0695**	0.151**
	(0.0815)	(0.0958)	(0.0698)	(0.0815)	(0.0309)	(0.0639)
z_tds			0.416**			
			(0.159)			
z_lnescost						1.444***
						(0.473)
Constant	-1.109***	-0.449**	-0.922***	-1.109***	-0.751***	-0.0240
	(0.172)	(0.212)	(0.191)	(0.172)	(0.0754)	(0.374)
Observations	295	295	295	295	295	295
R-squared	0.858	0.510	0.887	0.858	0.979	0.888
Number of id	27	27	27	27	27	27
controls	YES	YES	YES	YES	YES	YES
yearfix	YES	YES	YES	YES	YES	YES
idfix	YES	YES	YES	YES	YES	YES

Robust standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1

Table 5. Bootstrap Test Results

		Observered coefficient	Bootstrap std.err.	z	P>z	Normal-based [95% conf. interval]	
z_tds	Dir_Eff	0.0997162***	0.0373324	2.67	0.008	0.026546	0.1728863
	Ind_Eff	0.1517194***	0.058102	2.61	0.009	0.0378415	0.2655972
	Tot_Eff	0.2514355***	0.0623962	4.03	0.000	0.1291413	0.3737297
z_lnescost	Dir_Eff	0. 0687082**	0.0314288	2.19	0.029	0.0071089	0.1303074
	Ind_Eff	0.1827273***	0.0586591	3.12	0.002	0.0677575	0.2976971
	Tot_Eff	0.2514355***	0.0621984	4.04	0.000	0.1295289	0 .3733421

Robust standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1

4.3.3. Heterogeneity Analysis

Given the wide distribution and substantial differences among cities in the Yangtze River Delta region, this study evaluates the effectiveness of the talent introduction policy from three dimensions: city level, city location, and availability of higher education resources. Specifically, the analysis distinguishes between provincial capitals/municipalities versus other cities, eastern versus central cities, and cities with or without "211 Project" universities. The heterogeneity analysis results are presented in Table 6.

Table 6. Heterogeneity Analysis Results

	(1)	(2)	(3)	(4)	(5)	(6)
	City Level		City Location		Higher Education Resources	
VARIABLES	Provincial Capital or Municipality	Non-Provincial Capital or Municipality	Eastern City	Central City	With 211 University	Without 211 University
	z_agdp	z_agdp	z_agdp	z_agdp	z_agdp	z_agdp
did	0.253***	0.191	0.208*	0.0915	0.186**	0.0558
	(0.0885)	(0.106)	(0.107)	(0.113)	(0.0793)	(0.130)
Constant	-0.561	-3.149	-2.707***	0.520	-1.623***	-3.383
	(0.616)	(3.060)	(0.834)	(0.609)	(0.370)	(1.904)
Time Fixed	YES	YES	YES	YES	YES	YES
Individual Fixed	YES	YES	YES	YES	YES	YES
Control Variables	YES	YES	YES	YES	YES	YES
Observations	251	44	209	86	229	66
R-squared	0.845	0.978	0.884	0.964	0.909	0.960
Number of id	23	4	19	8	21	6

Robust standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1

4.3.3.1. Heterogeneity Analysis by City Level

Provincial capitals serve as political, economic, and cultural centers within their provinces, while municipalities hold significant positions on the national stage. These cities tend to have robust economic foundations and often lead development in surrounding areas. This study divides cities based on whether they are provincial capitals or municipalities. As shown in Table 7, Columns (1) and (2), the regression coefficient of the policy variable is significantly positive at the 1% level for provincial capitals or municipalities, whereas it is not significant for non-provincial or non-municipal cities. This indicates that talent introduction policies have a significant positive effect on the economic development of provincial capitals or municipalities, while the effect is not as pronounced in other cities.

4.3.3.2. Heterogeneity Analysis by City Location

Regional disparities in urban development remain prevalent in China. Given the unique characteristics of the sample, this study divides the cities into eastern and central regions for heterogeneity testing. As shown in Table 7, Columns (3) and (4), the estimated coefficient for eastern cities is significantly positive at the 10% level, whereas the coefficient for central cities is not significant. This suggests that talent introduction policies significantly enhance economic development in eastern cities, whereas the impact in central cities is not as evident. A potential reason for this regional heterogeneity is that eastern cities, with their locational and developmental advantages, established more comprehensive talent introduction systems earlier, allowing the policies to achieve greater effectiveness in implementation.

4.3.3.3. Heterogeneity Analysis by University Resources

Drawing from the approaches of other scholars, this analysis categorizes cities based on the presence of universities included in the "211" Project. As shown in Table 7, Columns (5) and (6), the estimated coefficient for cities with "211" universities is significantly positive at the 5% level, while the coefficient for cities without such universities is not significant. This indicates that talent introduction policies have a marked positive impact on the economic development of cities that host "211" universities, whereas the effects are not evident in cities without these institutions.

4.3.4. Baseline Regression with Other Dependent Variables

Based on the topic-word distributions derived from the LDA model, five major themes were summarized, and corresponding dependent variables were selected to replace $AGDP_{i,t}$ in the DID model for baseline regression.

Before regression, a parallel trend test was conducted. The results showed that variables such as scientific research funding, the measure of industrial structure advancement, and total fixed asset investment passed the test. However, the talent structure level and financial development level did not meet the criteria, potentially due to influences from other policies or the policies themselves not having significant effects.

The regression results are presented in Table 7. As indicated in Columns (1), (2), (5), and (6), regardless of whether control variables are included, and based on fixed time and individual effects, talent introduction policies positively influence the growth of scientific research funding and total fixed asset investment. This suggests that talent introduction policies encourage government increases in scientific research funding, which can drive sustained technological innovation in cities. Additionally, these policies positively impact total fixed asset investment, promoting entrepreneurship among urban enterprises.

Conversely, as shown in Columns (3) and (4), talent introduction policies have a negative impact on the measure of industrial structure advancement. This may be attributed to the close connection between industrial structure and China's economic policy reforms, which exhibit strong temporal characteristics. Between 2001 and 2009, the industrial structure in China did not show a trend toward advanced service-oriented development [16], resulting in a contradiction between talent introduction policies and the trajectory of industrial structure development.

Table 7. Other Dependent Variable Baseline Regression Results

VARIABLES	(1) z_lnscost	(2) z_lnscost	(3) z_ais1	(4) z_ais1	(5) z_fixinv	(6) z_fixinv
did	0.130*	0.141**	-0.221**	-0.139*	0.374**	0.316***
	(0.0695)	(0.0607)	(0.103)	(0.0754)	(0.144)	(0.111)
Constant	-0.880***	-0.780***	-0.528***	-0.460***	-0.667***	-1.299***
	(0.0349)	(0.103)	(0.0726)	(0.154)	(0.0864)	(0.408)
controls	NO	YES	NO	YES	NO	YES
yearfix	YES	YES	YES	YES	YES	YES
idfix	YES	YES	YES	YES	YES	YES
Observations	297	295	297	295	297	295
R-squared	0.950	0.959	0.602	0.835	0.702	0.810
Number of id	27	27	27	27	27	27

Robust standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1

5. Conclusion and Policy Recommendations

This study utilizes panel data from 27 prefecture-level cities and municipalities in the Yangtze River Delta region of China, focusing on talent introduction policies implemented between 2000 and 2010. By employing the LDA topic model to extract themes from policy documents and applying a multi-period DID model, we analyze the impact of talent introduction policies on urban development and the underlying mechanisms that empower economic growth. Based on the empirical results and text analysis presented above, the following research conclusions are drawn:

First, the text of the talent introduction policies, processed through the LDA topic model, reveals a theme-item distribution categorized into five major themes. It can be summarized that the talent introduction policies focus on five aspects: talent structure, industrial development, technological expenditure, financial development level, and innovation and entrepreneurship.

Second, the talent introduction policies have effectively promoted urban economic development, a conclusion that remains valid after robustness checks using PSM-DID models and double machine learning.

Third, the talent introduction policies not only promote urban economic development but also indirectly empower it by increasing government educational expenditure and enhancing financial development efficiency, providing a continuous impetus for urban economic growth.

Fourth, there are heterogeneous characteristics in the effects of talent introduction policies on urban economic development. Specifically, the enhancement in economic development is stronger in provincial capital or directly governed cities compared to non-provincial capital or directly governed cities; the effect is greater in eastern cities compared to central cities; and it is more pronounced in cities with abundant higher education resources than in those with fewer resources.

Fifth, the talent introduction policies have a significant positive effect on government technological expenditure and total fixed asset investment, while exhibiting a negative effect on the level of industrial structure. Additionally, there is no significant impact on talent structure level or financial development level.

Based on the above conclusions, this study offers the following insights:

First, it is crucial to continue implementing the current talent introduction policies while optimizing the measures for attracting talent. Empirical analysis indicates that talent introduction policies significantly promote urban economic development, government technological expenditure, and total fixed asset investment, while negatively affecting the level of industrial structure. Therefore, policies should maintain the positive aspects while adjusting the introduction strategies in accordance with the current economic conditions and industrial plans in China to achieve positive outcomes for industrial results. The lack of significant impact on talent structure level and financial development level suggests that the policies have not met the expectations of their formulators.

Consequently, it is essential to revise policy items related to improving talent structure and financial development, ensure effective policy implementation, and establish a robust mechanism to maximize policy effectiveness.

Second, it is important to fully consider the mediating effects of talent introduction policies on urban economic development, maximizing the combined effectiveness of talent policies and their mediating effects. In particular, considering the close relationship between policy benefits and financial development efficiency, the government should continuously improve credit risk-sharing mechanisms and investment financing systems to maintain smooth capital flow and enhance financial development efficiency, thereby laying a solid foundation for urban innovation and entrepreneurship. Additionally, the government needs to increase educational investment, improve student training systems, enhance student welfare, and ensure a conducive learning environment to empower the future development of cities.

Third, efforts should be made to enhance urban self-development through mutual learning and leveraging each other's strengths. Cities can identify their unique advantages and shortcomings compared to others, and develop a tailored talent introduction policy that suits their characteristics. For provincial capitals or directly governed cities, they should leverage their central positions in various aspects to actively innovate policies and serve as leaders and role models. For other cities or economically weaker central cities, there should be a focus on strengthening their economic capacity, optimizing industrial structures, and reasonably arranging subsequent measures for talent introduction to protect the basic rights of talent. For cities with weak higher education resources, active collaboration with external universities to establish research facilities and develop related incentive policies is essential to gradually gather higher education resources and empower urban development.

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