

## Can Talent Policies Attract Population Inflows? — An Empirical Analysis Based on Spatial Panel Modeling

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**Abstract** To analyze the spatial influence mechanism of talent policy on population flow, this study compares the government work reports of 31 provinces between 2008 and 2020, and quantifies regional talent policies in nine aspects, including talent evaluation and incentives, utilizing a comprehensive, standardized, and continuous approach. Additionally, this paper develops a spatial econometric analysis model and expands on the conventional neighborhood, distance, and economic matrices by constructing a spatial weight matrix that reflects talent flow. The findings indicate that population movement exhibits spatial clustering patterns. The regional government's talent policy, primarily based on talent evaluation and incentives, positively influences population inflow. Moreover, during the implementation of talent policies, local governments demonstrate cooperative relationships. The inter-regional spillover effect between talent evaluation and talent incentives is significantly positive. In other words, a stronger local talent evaluation policy, along with robust talent incentives, encourages population inflow from neighboring provinces. However, this conclusion may vary in different regions and over time. Recently, the spatial spillover effect of population inflow and the impact of talent policies have not shown significant results. Additionally, the attractiveness of talent evaluation in the eastern region surpasses that of talent incentives, while the opposite holds true for the central and western regions.

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This study investigates the impact of local government talent policies on population inflow and its spatial spillover effect, offering theoretical support for intergovernmental cooperation.

**Keywords** talent policy; population mobility; spatial econometric modeling

## 1 Presentation of the Issue

With rapid urbanization and eased household registration policies, China has seen a significant increase in interregional population movement. This large-scale movement has been instrumental in transferring material, information, technology, and capital. As a result, it has not only redefined the spatial distribution of the population but has also altered regional economic structures, industrial layouts, and resource and environmental conditions. This makes it one of China's most impactful geographic processes. The onset of China's large-scale population movement was between the 1980s and mid-1990s. During this period, many surplus rural workers, impacted by institutional reforms, shifted to urban non-agricultural sectors. The mobile population's annual growth rate then was around 7 percent. From the late 1990s to 2010, this growth rate climbed, averaging 12 percent annually. Historically, significant disparities in interprovincial population flows across regions have been noted. The primary movement direction was from less developed central and western provinces to more advanced eastern ones. The primary drivers for this movement include regional differences in industrial restructuring and fast-paced economic and social development (Cai<sup>[1]</sup>; Wang<sup>[2]</sup>). Besides these socio-economic drivers, other factors like migration distance, geographical features, and population size also played a part in influencing these population movements (Yang, et al.<sup>[3]</sup>; Duan<sup>[4]</sup>; Zhang and Cen<sup>[5]</sup>). However, a notable shift occurred post-2015, with populations moving back from the east to the west (Li, et al.<sup>[6]</sup>). Sichuan and Anhui provinces, in particular, witnessed a significant population return. This trend was largely influenced by various governmental policies encouraging workers to return to their native places for employment, fueling this return movement (Gu, et al.<sup>[7]</sup>). The role of regional government policies, especially those related to household registration, social security, enterprise employment, agricultural benefits, and financial support, is evident in influencing these patterns, as highlighted by several studies (Li<sup>[8]</sup>; Tian<sup>[9]</sup>; Cheng and Tan<sup>[10]</sup>).

Regarding talent policy implementation, ever since the Chinese Central Government launched the program to attract overseas top-tier talents, there's been a heightened state emphasis on bringing in such talents. This focus has led to a variety of dedicated policies aiming to attract and retain them, ensuring that the initiative continually evolves. Inspired by central government initiatives, provincial governments have unveiled their own talent introduction policies, complete with support measures. They aim to offer these talents considerable benefits, including development opportunities, platforms, living incentives, and logistical support, thereby increasing local appeal in the talent competition. However, a challenge persists: The prevailing employment system predominantly prioritizes local household registration given that resources are allocated based on the administrative stature of cities, coastal and developed eastern provinces have the lion's share. This imbalance creates stark regional disparities (Cai and Du<sup>[11]</sup>), making it challenging for central and western regions to compete for talents on equal grounds. The pressing questions now are how to effectively attract and properly place

talents, both critical for regional development. In 2016, the Central Committee of the Communist Party of China (CPC) published their views on furthering talent development system reforms. They urged local governments to eliminate talent mobility barriers and pursue proactive talent recruitment strategies. Subsequent regional talent recruitment events have garnered significant societal attention, leading some to term it a “war for talents” (Chen, *et al.*<sup>[12]</sup>). This shift also meant talent inflow and household registration migration metrics started to deviate. Scholars have since delved into this divergence from various angles. While many have investigated the evolution of China’s talent policy (Huang and Qu<sup>[13]</sup>; Luo and Tang<sup>[14]</sup>; Xue and Xie<sup>[15]</sup>) and how it influences regional innovation (Liu and Tian<sup>[16]</sup>; Zhong, *et al.*<sup>[17]</sup>), fewer have explored its impact on population and labor mobility. The majority of existing research evaluates the effects of regional economic factors and public services on population movement, often sidelining the role of talent policies (Wang, *et al.*<sup>[18]</sup>; Xia, *et al.*<sup>[19]</sup>). Current academic works tend to probe the effects of talent policy across sectors and formulate talent policy evaluation frameworks. While these insights inform this paper’s exploration into talent policy’s influence on population mobility decisions, there are evident gaps. A lot of the literature offers merely qualitative evaluations of talent policy’s implementation outcomes and improvement prospects, often overlooking a quantitative measure of its influence on population movements. Moreover, many studies simplify talent policy processes, neglecting holistic considerations like talent assessment, incentives, development, research management, innovation, and independent R&D. Finally, few account for the spillover effects between adjacent regions, potentially skewing the perceived attractiveness of a region for incoming populations.

In the given scenario, how influential are local talent policies in drawing population inflows? Do local governments compete or cooperate in this regard? To address these questions, this study meticulously analyzed government work reports from 31 provinces spanning 2008 to 2020. It then quantified regional talent policies from various dimensions. Subsequently, a spatial econometric model was developed. The findings indicate that among the myriad talent policies, only talent evaluation and talent incentive significantly bolster population inflow. Specifically, these two policies not only directly pull in populations but also indirectly promote population inflow due to the spillover effect. For every unit increase in population inflow, talent policy externalities contribute to about an additional 0.14 units. Robustness and endogeneity tests further reinforce the credibility of these primary regression findings. It’s evident that local governments’ efforts to attract external population inflows are influenced by both their own and other governments’ talent policies. However, this influence varies across space and time. Notably, in recent times, the spatial spillover effect of population inflow and the pull of talent policy have diminished. Furthermore, in the eastern region, enhancements in talent evaluation seem more enticing than talent incentives, whereas in the central and western areas, the reverse holds true. Distinguishing it from previous literature, this paper not only offers a multi-faceted, consistent, and comprehensive quantification of regional talent policy but also sheds light on the indirect impacts of neighboring regions’ talent policies. This insight fortifies the case for cooperative approaches among local governments.

## 2 Models and Data

### 2.1 Research Design

Regarding population mobility, conventional econometric models often overlook spatial correlation issues. In addressing this, spatial econometrics provides a more effective solution. Based on current established studies, the frequently employed spatial econometric models encompass the spatial lag model (SLM), the spatial error model (SEM), and the spatial Durbin model (SDM). Their respective formulas are presented below:

$$Y = \rho WY + X\beta + \epsilon, \quad (1)$$

$$Y = X\beta + \lambda W\mu + \epsilon, \quad (2)$$

$$Y = \rho WY + X\beta + WX\theta + \epsilon, \quad (3)$$

where  $Y$  is the dependent variable,  $X$  is the independent variable,  $W$  is the spatial weight matrix,  $WY$  is the spatial lag term of the dependent variable, which captures the effect of the dependent variable of the neighboring province on the dependent variable of the province,  $\beta$  is the coefficient of the independent variable,  $\rho$  is the coefficient of the spatial lag term  $WY$ ,  $WY$  is the coefficient of the spatial lag term of the independent variable, which captures the spatial effect of the explanatory variables of the neighboring provinces on the dependent variable of the province,  $\theta$  is the coefficient of the spatial lag term of the dependent variable. At that time  $\theta = 0$ , the SDM model is transformed into an SLM model, and at that time  $\theta + \rho\beta = 0$ , the SDM model is transformed into an SEM model,  $\epsilon$  is the residual term. To determine the appropriate spatial econometric model, this study employs hypothesis testing for spatially correlated maximum likelihood estimation and its robust form. The spatial autocorrelation test reveals that from 2008 to 2020, the Moran index of population flow in China for each year is significantly correlated at the 1% level. This signifies that the population flow in different regions of China exhibits significant spatial autocorrelation throughout the examined period, justifying the choice of the spatial measurement model. To further select an appropriate spatial model, the paper employs a combination of the “specific to general” and “general to specific” approaches, utilizing LM test, Hausman test, LR test, and Wald test. The results indicate that the LM-error and Robust-LM-error values are 12.228 and 0.975, respectively. The latter result is not significant, confirming the acceptance of the original hypothesis. However, the values of LM-lag and Robust-LM-lag are 23.336 and 12.083, respectively, both of which are significant at the 1% level, leading to the rejection of the original hypothesis. As a result, this paper selects the spatial lag model (SAR).

The study employs five spatial weight matrices for selection. The first matrix (W1) represents adjacency, with a weight of 1 for adjacent places and 0 for non-adjacent ones. The second matrix (W2) represents geographic distance, with weight values as reciprocals of distances from provincial capitals. The third matrix (W3) represents economic distance, with weight values proportional to the difference in economic levels between places. The fourth matrix (W4) combines economic and social factors, with weight values as the quotient of economic level dif-

ferences and the square of the inverse distance between provincial capitals. These matrices<sup>1</sup> partly reflect the spatial connections of the research topic. However, due to their lack of clear meaning, this paper also attempts to construct a spatial weight matrix based on the gravity model. This model, rooted in classical mechanics and established by geographers, sociologists, and economists, explains how human interactions occur in geographic space economically, socially, and politically. The gravity model has been widely used to measure international trade flows and population migration, making it the dominant model for measuring spatial interactions. The talent mobility matrix expresses the strength of spatial linkages for talent and is represented by the formula:

$$w_{ij} = \begin{cases} kM_iM_j/D_{ij}, & i \neq j \\ 0, & i = j \end{cases} \quad (4)$$

where  $w_{ij}$  represents the strength of spatial linkages of elements between places and localities;  $k$  is a constant, usually taken as 1;  $M_i$  and  $M_j$  represent the number of talents in Place  $i$  and Place  $j$ , respectively, and are expressed in this paper as full-time equivalents of R&D personnel;  $D_{ij}$  represents the distance between the center locations of the two regions, Local  $i$  and Local  $j$ . The formula provided above helps measure the strength of the annual talent flow's spatial linkage. To consider the flow of talents in different places, the paper constructs a spatial weight matrix using the average number of talents from 2008 to 2020. Since the spatial weight matrix is considered an exogenous variable, it is essential to include it fully in the analysis.

## 2.2 Variables and Data

In the available public data system, population flow and migration data are only available at the provincial level. To investigate whether talent policies significantly influence population flow decisions and how this influence varies across regions, this study focuses on the inter-provincial population flow of 31 provinces, autonomous regions, and municipalities directly under the central government of mainland China (excluding Hong Kong, China; Macao, China and Taiwan, China). The analysis is based on the data from the national census of 2010 and 2020, along with relevant economic and social data. The study examines the scale and flow characteristics of inter-provincial population movements during the period of 2008–2020, which aligns with the time span of the talent policy implementation over these 13 years.

### 2.2.1 Explained Variable: Population Inflow

Expressed as the net population inflow rate ( $Y_1$ ), which is the ratio of the net inflow to the number of people at the beginning of the year, all types of populations considered in this paper refer to the resident population. Regarding inter-provincial population flows, at the beginning of the sample period, the eastern provinces of Beijing, Tianjin, Shanghai, and Guangdong experienced significant population inflows, with net inflow rates of 5.31 percent, 5.25 percent, 3.45 percent, and 1.68 percent, respectively. On the other hand, provinces like Guizhou,

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<sup>1</sup>The geographic distance matrix can be expressed as  $w_{ij} = 1/d_{ij}$ , representing the reciprocal of the distance between the two place. The economic spatial weighting matrix, denoted  $w_{ij} = (1/|x_i - x_j|) \div (\sum_j 1/|x_i - x_j|)$ , represents the share of the total difference in economic levels between the two locations.

Gansu, Qinghai, Anhui, Heilongjiang, Hunan, Shaanxi, and Sichuan witnessed net population emigration until around 2014. However, after 2015, the developed provinces, represented by Beijing, Tianjin, and Shanghai, became less attractive for population inflow, and there was a gradual shift of population towards western regions represented by Xinjiang, Sichuan, and Tibet. This shift might be related to the implementation of talent policies in central and western regions.

Regarding the total amount of population flow, from 2008 to 2020, provinces such as Heilongjiang, Anhui, Jilin, Hubei, Jiangxi, Guangxi, and Gansu experienced more significant population outflows. Heilongjiang and Anhui, in particular, had cumulative population outflows of 6,680,300 and 5,127,400, respectively, during the examined period. On the other hand, Guangdong, Zhejiang, and Jiangsu were the provinces that absorbed the largest inflows of people, with their total population flows reaching 19,238,400, 9,638,200, and 5,132,300, respectively. In recent years, hotspots of population inflow have been concentrated in the provinces of Fujian, Zhejiang, Anhui, and Hubei. These regions are experiencing increasing competition in the industrial and labor markets due to economic transformation. Additionally, the introduction of relevant incentives by various levels of government has facilitated large-scale population inflows in recent years.

### 2.2.2 Explanatory Variable: Talent Policy

Upon reviewing recent talent policies, it is evident that these policies can be categorized into several main areas, including talent cultivation, talent introduction, talent incentives, talent evaluation, talent mobility, talent services, as well as policies related to scientific research system and mechanism reform, innovation and entrepreneurship environment cultivation, and enhancing independent research and development capabilities (Luan and Zhang<sup>[20]</sup>; Zhu, et al.<sup>[21]</sup>).

In this study, we will assess the talent policy based on these nine aspects, breaking down the talent policy into specific areas: Introduction of high-level talents (INT), talent evaluation (EVA), talent incentives (AWA), talent mobility (FLO), talent cultivation (CUL), talent services (SER), scientific research management (ADM), innovation and entrepreneurship (INN), and independent research and development (RD). We have further subdivided some indicators based on relevant literature and policies. For instance, the talent incentive policy includes two secondary variables: Income from transformation of achievements and remuneration-related policies. The talent cultivation policy has three secondary variables: Policies related to the cultivation of skilled personnel, vocational education, and higher education. The scientific research management policy contains three secondary variables: Policies related to institutional reforms, project management, and scientific research funding. The innovation and entrepreneurship policy has three secondary variables: Policies related to space, funding, and services. Lastly, the independent research and development policy comprises three secondary variables: Policies related to major special projects, R&D funding, and infrastructure construction. Considering the significant variation in frequency, quantity, and style of talent policies among different provinces, and recognizing that government work reports hold high authority and have characteristics of continuity and standardization, this study uses the government work reports from 2008 to 2020

of all 31 provinces (autonomous regions and municipalities) as a sample for measuring talent policies. We follow the quantitative criteria for innovation policies set by Peng, et al.<sup>[22]</sup>, and Chen, et al.<sup>[23]</sup>, emphasizing specific values and plans. The explanatory variables' connotations and extensions are continuously clarified, and evaluation criteria are revised through multiple back-to-back scoring. Each of the four primary variables without secondary variables and the 14 secondary variables were evaluated using roughly the same criteria. Content with specific values, names, or measures in this year's work received 5 points; content with a development direction and more detailed mark received 4 points; content mentioned but not detailed in this year's work received 3 points; content mentioned only in the previous year's work review received 2 points; and content not mentioned at all received 1 point. To synthesize secondary variables into primary variables, we used the equal weight assignment method. Considering the lack of significant interaction between variables, we employed the linear synthesis method.

### 2.2.3 Control Variables

The remaining control variables chosen in this study primarily represent regional characteristics, including the level of economic development (GDP, represented by per capita real GDP), industrial structure (IS, denoted by the proportion of tertiary industry added value), foreign exchange level (OPEN, signified by the import and export proportion to GDP), government influence (FE, expressed by the fiscal expenditure proportion to GDP), technological innovation capability (INNO, indicated by the R&D expenditure proportion to GDP), education, sports, and environmental construction (EDU, represented by the proportion of expenditures on education, sports, social security, healthcare, and environment to fiscal expenditures), infrastructure development (FS, denoted by per capita urban road area), and urban density (PD, signified by urban population density). Table 1 displays the statistical descriptions of each variable, with the maximum variance inflation factor for each variable being 5.00, which is below the typical threshold of 10, and thus not considered to exhibit multicollinearity. (Additionally, the absolute value variables of real GDP per capita, urban road area per capita, and urban density are decentered in this paper's empirical analysis.)

## 3 Empirical Analysis

### 3.1 Return to Baseline

This study initially examines the impact of talent policies on the net population inflow rate using a fixed-effects model. The findings indicate that only talent evaluation and talent incentives have a significant positive influence on population inflow. On the other hand, high-level talent introduction, talent mobility, talent cultivation, talent services, scientific research management, innovation and entrepreneurship, and independent research and development policies do not significantly affect the net population inflow rate. After considering spatial spillover effects using different spatial weight matrices, talent evaluation and talent incentive policies continue to show a significant impact on population inflow. Thus, the remaining seven variables are not considered in subsequent model<sup>2</sup> analyses. This might be due to the operational

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<sup>2</sup>The results are detailed in Appendix.

**Table 1** Descriptive statistics

Symbols	Variable Description	Observations	Average value	Standard deviation	Minimum value	Maximum value	VIF
Y1	Net population in inflow rate	403	0.15	1.15	−5.91	5.51	-
Y2	Net inflow of population (10,000 persons)	403	4.88	47.83	−286.94	250.35	-
INT	Introduction of high level talents	403	3.42	0.85	1.00	5.00	1.48
EVA	Talent evaluation	403	2.56	0.92	1.00	4.00	1.69
AWA	Talent Incentives	403	2.67	0.66	1.00	4.00	1.61
FLO	Talent mobility	403	2.57	0.85	1.00	4.00	1.42
CUL	Talent Development	403	3.17	0.57	1.00	4.67	1.20
SER	Talent Services	403	3.08	0.61	1.00	5.00	1.12
ADM	Talent Management	403	2.87	0.52	1.33	5.67	1.45
INN	Innovation and Entrepreneurship	403	2.98	0.64	1.00	4.67	1.82
RD	Self-developed	403	2.72	0.55	1.00	4.00	1.76
GDP	Real GDP per capita (RMB 10,000/person)	403	4.05	2.07	0.88	12.14	5.00
IS	Share of tertiary sector	403	0.45	0.10	0.29	0.84	3.76
OPEN	Imports and exports as a share of GDP	403	0.27	0.32	0.01	1.80	3.53
FE	Percentage of financial expenditure	403	0.27	0.20	0.09	1.38	3.61
INNO	Industrial enterprises above scale R&D expenditure as a proportion of GDP	403	0.01	0.01	0.01	0.02	3.55
EDU	Financial share of expenditure on education, culture, sports, and environment development	403	0.47	0.06	0.27	0.58	2.61
FS	Urban road area per capita	403	15.09	4.75	4.04	26.78	1.80
PD	Urban density	403	2808.11	1188.05	515	5967	1.30

Note: This study utilizes information from China's government work reports, which are released at the beginning of each year and focus on the "main tasks of the year," while statistical yearbooks contain information at the end of the year. Therefore, there is a one-year lag in the data, and the period of statistical data in this study covers the years 2008–2020. The information is sourced from previous editions of the China Science and Technology Statistical Yearbook and China Statistical Yearbook, among others.



nature and broader coverage of talent evaluation and talent incentive policies, making them more effective in attracting population inflows directly.

Table 2 presents the results focusing on talent evaluation, talent incentives, and other control variables. Model 1 utilizes a fixed-effects model, while Models 2 to 6 use a spatial lag model with various spatial weighting matrices: Neighborhood matrix, inverse distance matrix, economic distance matrix, economic and social matrix, and talent flow matrix, respectively. In all these models, the regression coefficients of talent evaluation and talent incentives are statistically significant at the 1% level, indicating that talent policies can attract population inflow by

**Table 2** Return to baseline

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
	Fixed Effect	Adiacenty Matrix	Inverse Distance Matrix	Economic Matrix	Economic and Social Matrix	Talent Mobility Matrix
<i>P</i>		0.259*** (0.062)	0.401*** (0.112)	0.253*** (0.086)	0.365*** (0.065)	0.230*** (0.087)
EVA	0.159*** (0.060)	0.155*** (0.054)	0.164*** (0.054)	0.148*** (0.055)	0.129** (0.053)	0.149*** (0.055)
AWA	0.185*** (0.073)	0.174*** (0.067)	0.177*** (0.067)	0.189*** (0.067)	0.171*** (0.065)	0.202*** (0.067)
GDP	-0.292* (0.151)	0.0683 (0.196)	-0.0202 (0.199)	0.0705 (0.198)	0.101 (0.192)	0.0566 (0.199)
IS	-3.898*** (1.087)	-2.891** (1.406)	-2.991** (1.421)	-3.071** (1.421)	-2.644* (1.379)	-3.331** (1.423)
OPEN	3.404*** (0.502)	3.409*** (0.480)	3.595*** (0.479)	3.487*** (0.488)	3.054*** (0.480)	3.572*** (0.486)
FE	1.737 (1.213)	3.825*** (1.377)	3.741*** (1.392)	3.795*** (1.392)	3.701*** (1.349)	3.843*** (1.400)
INNO	95.93*** (27.103)	106.9*** (25.380)	123.1*** (25.597)	113.9*** (25.569)	99.83*** (24.942)	117.1*** (25.676)
EDU	0.725 (1.572)	-0.128 (1.651)	-0.0806 (1.670)	-0.0546 (1.670)	0.0546 (1.618)	-0.117 (1.618)
FS	0.244** (0.112)	0.298*** (0.109)	0.320*** (0.110)	0.286*** (0.111)	0.261*** (0.107)	0.281** (0.112)
PD	-0.508*** (0.108)	-0.438*** (0.099)	-0.449*** (0.100)	-0.473*** (0.100)	-0.445*** (0.097)	-0.478*** (0.100)
<i>R</i> <sup>2</sup>	0.434	0.556	0.559	0.52	0.544	0.535
Log1	-	-404.39	-404.04	-407.08	-398.54	-409.29
<i>N</i>	403	403	403	403	403	403

Note: The values in brackets are standard errors. \**p* < 0.1, \*\**p* < 0.05, \*\*\**p* < 0.01.

emphasizing these aspects. The coefficient  $\rho$  also holds significance at the 1% level, indicating the existence of a spillover effect in population inflow. Specifically, an increase in population inflow from neighboring areas leads to an increase in local inflow. Across Models 2 to 6, the average spillover effect of population inflow is 0.302. The direct effect of talent evaluation is 0.149, implying that a 1-unit improvement in talent evaluation policy results in a 0.149-unit increase in the population inflow rate. Similarly, the direct effect of talent incentives is 0.183, showing that a 1-unit improvement in talent incentives leads to a 0.183-unit increase in the population inflow rate. Additionally, talent policies indirectly contribute to the population inflow rate through the spillover effect of population inflow. This can be estimated as  $0.149 \times 0.302 / (1 - 0.302) = 0.06$  and  $0.1183 \times 0.302 / (1 - 0.302) = 0.08$  for talent evaluation and talent incentives, respectively. This suggests that for every unit increase in population inflow, approximately 0.14 units of population inflow are induced by population policy externalities. It is evident that the local government's efforts to attract population inflow are positively influenced by talent policies implemented by other governments.

Regarding the control variables, most of them are statistically significant at the 1% or 5% level, except for the level of local economic development, education, culture, sports, and environmental development. The differences in talent policies among provinces have made these aspects less influential in attracting population inflow. The increase in the share of fiscal expenditure and R&D expenditures of industrial enterprises above large scale in GDP positively impact population inflow. Moreover, the level of openness to the outside world and infrastructure development also play essential roles in attracting more inflows, while population density can lead to congestion in cities, making them less attractive for population inflow.

### 3.2 Robustness Check

The above empirical results demonstrate that talent policy implementation positively influences population inflow, primarily through talent evaluation and talent incentives. However, to ensure the reliability of these results, further verification is necessary. This study examines the robustness of the findings by performing various tests: replacing core variables, changing the spatial weighting matrix, and using different methodologies. Table 3 presents different models used for verification. Models 1 and 2 assess the impact of talent policies on population mobility by substituting the explanatory variables and using the total population at the end of the year as the denominator of the net population inflow rate. Models 3 and 4 involve changing the spatial weighting matrix and reconstructing the talent flow matrix based on the average number of talents for 2008–2014 and 2015–2020, respectively. Models 5 and 6 re-examine the effect of talent policy on population inflow using a spatial Durbin model and a spatial error model, respectively. The empirical results reveal that the direction and significance of the coefficients for core variables, such as the spatial aggregation effect of population inflow, talent evaluation, and talent incentives, remain consistent with the previous findings. Thus, the empirical results are highly robust.

### 3.3 Endogeneity Test

Since population inflow tends to have a continuous character, this paper introduces population inflow in the lagged period as an explanatory variable. It is worth noting that in addition

**Table 3** Robustness check 1

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
	Replacement of variables	Replacement of variables	Change Matrix	Change Matrix	SDM	SLM
$P$	0.242*** (0.062)	0.391*** (0.114)	0.232*** (0.087)	0.162** (0.065)	0.220*** (0.068)	
$\lambda$						0.224*** (0.070)
EVA	0.002*** (0.001)	0.002*** (0.001)	0.001*** (0.001)	0.001*** (0.001)	0.142*** (0.054)	0.162*** (0.054)
AWA	0.002*** (0.001)	0.002*** (0.001)	0.002*** (0.001)	0.002*** (0.001)	0.157** (0.067)	0.162** (0.068)
GDP	0.001 (0.002)	-0.001 (0.002)	0.001 (0.002)	0.001 (0.002)	-0.024 (0.209)	0.046 (0.200)
IS	-0.029** (0.014)	-0.030** (0.014)	-0.033** (0.014)	-0.032** (0.014)	-3.008** (1.431)	-3.047** (1.395)
OPEN	0.033*** (0.005)	0.035*** (0.005)	0.034*** (0.005)	0.034*** (0.005)	3.057*** (0.507)	3.574*** (0.491)
FE	0.037*** (0.014)	0.036*** (0.014)	0.037*** (0.014)	0.035** (0.014)	4.592*** (1.472)	3.818*** (1.418)
INNO	1.061*** (0.253)	1.210*** (0.255)	1.156*** (0.255)	1.209*** (0.256)	92.22*** (26.598)	110.4*** (26.006)
EDU	-0.0011 (0.016)	-0.001 (0.017)	-0.001 (0.017)	-0.002 (0.017)	-0.609 (1.678)	0.0785 (1.678)
FS	0.003*** (0.001)	0.003*** (0.001)	0.003** (0.001)	0.003** (0.001)	0.246** (0.113)	0.332*** (0.111)
PD	-0.004*** (0.001)	-0.004*** (0.001)	-0.005*** (0.001)	-0.004*** (0.001)	-0.459*** (0.106)	-0.443*** (0.098)
$R^2$	0.550	0.514	0.527	0.535	0.407	0.540
Logl	1452.69	1450.71	1448.99	1448.77	-398.211	-407.71
$N$	403	403	403	403	403	403

Note: The values in brackets are standard errors. \* $p < 0.1$ , \*\* $p < 0.05$ , \*\*\* $p < 0.01$ ; The spatial weight matrices used in Models 1 and 2 are the adjacency and inverse distance matrices, respectively; the spatial weight matrices used in Models 3 and 4 are the talent flow matrices; and the spatial weight matrices used in Models 5 and 6 are the adjacency matrices. Limited to space, this paper does not report the regression results under other weighting matrices, but the direction and significance of the coefficients of the core variables therein are the same as those in the benchmark regression.

to the endogeneity problem due to the first-order lagged term of population mobility being introduced as an explanatory variable, this paper is challenged by the endogeneity problem due to the bidirectional causality between population mobility and talent policy. At this point, the least squares (OLS) estimates are biased and inconsistent. Therefore, the choice of an appropriate estimation method will be the focus of empirical estimation. In the choice of estimation methods, considering the weak robustness and other problems of the great likelihood method and the proposed great likelihood method, this paper adopts the systematic GMM method to estimate the parameters of the dynamic spatial panel model constructed in Eq.(5), which is able to select the appropriate instrumental variables from the time-trend changes of the variables.

$$Y = \rho WY + \gamma L.Y + X\beta + \epsilon, \quad (5)$$

where  $L.Y$  represents the first order lag term of the explanatory variables. In Table 4, the dynamic spatial lag model was used for Models 1~5, whose spatial weight matrices were the adjacency matrix, inverse distance matrix, economic distance matrix, economic and social matrix, and talent flow matrix, respectively. From the test results, the correlation tests are passed, indicating that it is more reasonable to choose the spatial Durbin model. In this case, the statistic results of AR(2) all exceed 0.1, indicating that the hypothesis of the absence of second-order autocorrelation was not rejected. The results of the Sargan test for over constraint identification indicate that the choice of instrumental variables is valid overall. From the coefficients, population movement still has a significant spatial agglomeration effect under the dynamic spatial lag model; At the same time, the relationship between population flows in the lagged period and those in the current period is significantly positive at the 1 percent level, which suggests that there is a certain degree of “continuity” in population flows and that the inflow of population in the local lagged period will lay the foundation for the inflow of population in the current period. Regarding the impact effect of talent policies, the impact coefficients of talent evaluation and talent incentives are significantly positive at the 1 percent or 5 percent level in all models, except for model 5, where the coefficient of talent evaluation is negative but not significant, which is consistent with the findings in the benchmark regression.

### 3.4 Analysis of Spatio-Temporal Heterogeneity

#### 3.4.1 Analysis of Temporal Heterogeneity

In 2016, the Central Committee of the Communist Party of China (CPC) released the Opinions on Deepening the Reform of the Talent Development System. This document urged local governments to eliminate obstacles to talent movement and to adopt aggressive and effective talent acquisition strategies. Following this, provinces conducted talent recruitment conferences. New first-tier and second-tier cities publicly announced their talent acquisition goals, leading to significant public interest. This phenomenon is termed the “war for talent”. The current research examines the link between talent policies and population influx in two distinct phases, using 2016 as the dividing point. Table 5 presents regression outcomes: Models 1~3 focus on the period 2008–0016, but due to space constraints, only results related to the adjacency matrix, inverse distance matrix, and talent flow matrix are detailed. Models 4~6 concentrate

on the period 2017–2020.

**Table 4** Robustness check 2

	Model 1	Model 2	Model 3	Model 4	Model 5
	Adjacency Matrix	Inverse Distance Matrix	Economic Matrix	Economic and Social Matrix	Talent Mobility Matrix
<i>P</i>	0.115*** (0.033)	0.374*** (0.039)	1.009*** (0.195)	4.221*** (0.278)	0.001*** (0.000)
<i>LY1</i>	0.100*** (0.018)	0.0490** (0.019)	0.0429*** (0.016)	0.0320** (0.013)	0.417*** (0.037)
<i>EVA</i>	0.0894*** (0.020)	0.0638** (0.029)	0.0429 (0.029)	0.0726*** (0.022)	−0.0503 (0.065)
<i>AWA</i>	0.148*** (0.044)	0.121** (0.058)	0.104** (0.049)	0.128** (0.050)	0.155* (0.083)
<i>GDP</i>	−0.247 (0.159)	−0.267*** (0.094)	−0.201* (0.104)	−0.252** (0.098)	−0.157*** (0.054)
<i>IS</i>	−2.818 (1.935)	1.159 (1.663)	−2.558** (1.274)	−0.174 (1.410)	−0.0555 (0.558)
<i>OPEN</i>	3.439*** (0.678)	1.891*** (0.249)	1.731*** (0.445)	1.129** (0.444)	0.869** (0.343)
<i>FE</i>	1.497 (1.067)	1.951*** (0.726)	1.763** (0.765)	1.369*** (0.467)	0.404 (0.922)
<i>INNO</i>	−26.05 (22.397)	45.31* (24.572)	47.28** (20.557)	36.93* (21.384)	15.77 (16.500)
<i>EDU</i>	0.868 (1.528)	−0.323 (1.317)	1.754 (1.212)	1.319 (0.870)	−0.151 (0.662)
<i>FS</i>	0.355** (0.142)	0.367*** (0.070)	0.140 (0.101)	0.0806 (0.109)	−0.0262 (0.051)
<i>PD</i>	−0.176*** (0.066)	−0.0965** (0.048)	−0.191*** (0.050)	−0.218*** (0.064)	−0.162 (0.130)
<i>Cons</i>	−0.737 (1.219)	−2.470*** (0.653)	−1.371 (0.891)	−2.062** (0.881)	−0.706** (0.339)
<i>N</i>	372	372	372	372	372

Note: The values in brackets are standard errors. \* $p < 0.1$ , \*\* $p < 0.05$ , \*\*\* $p < 0.01$ ; Two-step GMM is used for estimation in the model, while the instrumental variables are selected with up to 2nd order lags, and the collapse technique is used to limit them with respect to their number.

**Table 5** Tests for temporal heterogeneity

	first stage: 2008–2016			second stage: 2017–2020		
	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
	Adjacency Matrix	Inverse Distance Matrix	Talent Mobility Matrix	Adjacency Matrix	Inverse Distance Matrix	Talent Mobility Matrix
<i>P</i>	0.230*** (0.078)	0.386*** (0.143)	0.209** (0.106)	−0.068 (0.126)	−0.333 (0.342)	0.020 (0.187)
EVA	0.160** (0.069)	0.165** (0.069)	0.154** (0.070)	−0.0636 (0.061)	−0.0659 (0.060)	−0.0629 (0.061)
AWA	0.196** (0.087)	0.197** (0.087)	0.216** (0.087)	0.012 (0.081)	0.011 (0.080)	0.007 (0.081)
GDP	0.050 (0.399)	−0.120 (0.397)	−0.099 (0.400)	−0.788*** (0.252)	−0.786*** (0.251)	−0.783*** (0.252)
IS	−4.154* (2.133)	−4.185* (2.146)	−4.530** (2.153)	2.830 (1.971)	2.833 (1.961)	2.776 (1.972)
OPEN	3.632*** (0.634)	3.801*** (0.630)	3.776*** (0.638)	1.602 (1.289)	1.577 (1.271)	1.735 (1.270)
FE	3.938** (1.787)	3.806** (1.799)	4.038** (1.807)	−3.419* (1.956)	−3.327* (1.950)	−3.401* (1.964)
INNO	70.35 (44.321)	87.63** (44.461)	84.92* (44.675)	−60.37 (50.563)	−60.94 (50.349)	−60.05 (50.662)
EDU	−0.487 (2.228)	−0.675 (2.239)	−0.758 (2.251)	−4.513* (2.388)	−4.454* (2.379)	−4.530* (2.403)
FS	0.199 (0.187)	0.232 (0.189)	0.176 (0.190)	−0.439*** (0.132)	−0.454*** (0.133)	−0.433*** (0.132)
PD	−0.502*** (0.142)	−0.504*** (0.143)	−0.545*** (0.143)	0.0170 (0.141)	0.0117 (0.141)	0.0193 (0.142)
$R^2$	0.579	0.546	0.554	0.123	0.122	0.122
Logl	−296.52	−297.50	−298.78	−31.79	−31.45	−31.93
<i>N</i>	279	279	279	124	124	124

Note: The values in brackets are standard errors. \* $p < 0.1$ , \*\* $p < 0.05$ , \*\*\* $p < 0.01$ .

It's evident that the spatial clustering of population inflows differs between these phases. From 2008–2016, spatial spillover effects of population inflows were consistently positive, significant at either the 1% or 5% level. However, there were no significant spatial spillovers for the 2017–2020 period. This indicates that the previous “demonstration effect” of population influx is no longer evident in the current “war for talent” scenario. Additionally, during 2008–2016, both talent evaluation policies and incentive strategies had a significant positive impact, align-

ing with benchmark regression results. It suggests that enforcing talent policies could effectively attract population inflows during this time. However, the effectiveness of these talent policies diminishes between 2017–2020. A plausible reason might be that with the ongoing “war for talent”, various regions have initiated similar talent policies. This has resulted in a decreased distinctiveness in talent evaluation and incentive strategies, thus, making them less appealing for population inflow. It underscores the value of having distinct talent policies.

### 3.4.2 Analysis of Spatial Heterogeneity

Economic development varies across the country’s regions, influencing their appeal for population migration. Currently, the coastal eastern region displays a “high-high” population inflow trend, while the inland central and western regions exhibit a “low-low” pattern. Does this imply that talent policies impact regions differently? To investigate this, the study breaks the sample into two: One for the eastern region and one for the midwestern region. Regression results for the eastern region are displayed as Models 1~3 in Table 6. Due to space constraints, only outcomes from the adjacency matrix, inverse distance matrix, and talent flow matrix are presented. Meanwhile, Models 4~6 report findings for the central and western regions.

Table 6’s empirical outcomes, spanning Models 1~6, reveal varying spatial spillover effects of population inflows across regions. Overlooking the objective weights of talent mobility and considering just geographical closeness, the eastern region shows a significant spatial clustering of population inflow. However, this prominence fades under the talent mobility matrix. Generally, regression outcomes for the eastern region are congruent with baseline findings, pointing towards a positive clustering of population influx. For the western region, the spatial spillover effect isn’t notable in Models 4 and 6, yet it turns significantly negative in Model 5. This could be because many central and western provinces are expansive, making border adjacency less influential in determining population linkages. Consequently, the spatial weights in the neighborhood matrix become less relevant than the inverse distance matrix. Just as with the eastern region, the spatial spillover effect of population inflow loses significance when accounting for objective talent mobility weights. The disparity in spatial spillover effects between Models 2 and 5 highlights diverse population inflow patterns in the eastern versus central and western regions. Regarding population policy, the eastern region’s talent evaluation policy positively influences population inflow, but the talent incentive policy’s impact is negligible. In contrast, the central and western regions primarily boost population inflow via talent incentives. This variation might stem from the eastern region’s more robust talent incentive policy, making incoming populations prioritize talent evaluation there. Conversely, as the western region’s talent incentive policy is less developed, bolstering these incentives effectively attracts people, rendering talent evaluation less influential in this context.

**Table 6** Tests for spatial heterogeneity

	Eastern region			Central and Western region		
	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
	Adjacency Matrix	Inverse Distance Matrix	Talent Mobility Matrix	Adjacency Matrix	Inverse Distance Matrix	Talent Mobility Matrix
<i>P</i>	0.289*** (0.076)	0.224* (0.122)	0.117 (0.123)	−0.008 (0.092)	−1.062*** (0.297)	0.116 (0.113)
EVA	0.306*** (0.100)	0.287*** (0.104)	0.271*** (0.105)	0.0781 (0.063)	0.0813 (0.060)	0.0720 (0.063)
AWA	0.129 (0.160)	0.184 (0.166)	0.229 (0.167)	0.178** (0.074)	0.169** (0.070)	0.179** (0.074)
GDP	−0.632** (0.305)	−0.846*** (0.314)	−0.760** (0.323)	0.427 (0.362)	0.481 (0.344)	0.455 (0.361)
IS	−6.619** (3.376)	−5.796* (3.503)	−5.088 (3.593)	−1.631 (1.618)	−1.766 (1.529)	−1.568 (1.603)
OPEN	2.985*** (0.619)	2.923*** (0.643)	2.814*** (0.660)	1.837 (1.239)	1.776 (1.175)	1.905 (1.234)
FE	−5.417 (5.240)	−9.547* (5.293)	−9.724* (5.428)	3.405** (1.551)	3.565** (1.473)	3.418** (1.544)
INNO	189.1*** (36.634)	219.3*** (36.965)	220.3*** (37.628)	27.01 (41.347)	21.17 (39.277)	26.75 (41.153)
EDU	−4.246 (2.743)	−4.405 (2.854)	−4.189 (2.896)	0.987 (2.238)	0.784 (2.124)	1.061 (2.227)
FS	0.378 (0.231)	0.391 (0.241)	0.339 (0.246)	0.158 (0.143)	0.110 (0.137)	0.146 (0.143)
PD	−1.035*** (0.227)	−1.080*** (0.236)	−1.068*** (0.240)	−0.360*** (0.111)	−0.381*** (0.105)	−0.369*** (0.110)
<i>R</i> <sup>2</sup>	0.135	0.128	0.121	0.234	0.203	0.231
Logl	−114.87	−119.79	−120.93	−257.31	−250.45	−256.80
<i>N</i>	143	143	143	260	260	260

Note: The values in brackets are standard errors. \* $p < 0.1$ , \*\* $p < 0.05$ , \*\*\* $p < 0.01$ ; The Eastern Region includes 11 provinces (municipalities directly under the central government): Beijing, Tianjin, Hebei, Liaoning, Shanghai, Jiangsu, Zhejiang, Fujian, Shandong, Guangdong, and Hainan.

## 4 Conclusions and Policy Recommendations

To delve into the influence of talent policy on population mobility within provinces, this study reviews government reports from 31 provinces between 2008 and 2020. It quantifies regional talent policies in nine areas, including talent evaluation and incentives, subsequently



forming a spatial econometric model. The findings indicate that talent policies positively impact population inflow, primarily via talent evaluation and incentives. Furthermore, these policies indirectly augment the population inflow rate through a spillover effect. Specifically, for each unit increase in population inflow, policy externalities contribute to an approximate rise of 0.14 units. Robustness and endogeneity tests further corroborate the benchmark regression outcomes. It's evident that local administrations are influenced by both domestic and foreign talent policies when seeking external population inflows. Nevertheless, this influence varies spatially and over time. Notably, in recent years, both the spatial spillover effect of population inflow and the draw of talent policies have dwindled in significance. Moreover, in the eastern region, talent evaluation policies hold greater allure than incentives, whereas the inverse is true in the central and western areas.

Given these modeling outcomes, the study suggests several policy recommendations: Local governments should collaborate on talent policies to foster a positive spatial spillover effect. Beyond competition, there exists inherent cooperation among provinces in attracting population. Establishing synergistic and complementary talent policies within a region can promote harmonious inter-provincial development. Local authorities should devise unique talent policies aligned with their developmental goals. Amidst the war for talent, generic talent policies become less enticing for populations. Tailored policies, based on a province's specific circumstances, should be enacted. The eastern region should refine its talent evaluation mechanisms to foster a sense of belonging for incoming populations. Meanwhile, the central and western provinces should prioritize enhancing talent incentives, particularly focusing on policies around income and rewards for achievement conversions.

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## Appendix

**Appendix 1** Benchmark regressions considering all talent policies

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
variant	FE	Adjacency Matrix	Inverse Distance Matrix	Economic Matrix	Economic and Social Matrix	Talent Mobility Matrix
<i>P</i>	— (0.062)	0.259*** (0.114)	0.395*** (0.086)	0.260*** (0.065)	0.364*** (0.087)	0.245***
INT	0.024 (0.058)	−0.016 (0.053)	−0.015 (0.053)	−0.005 (0.053)	−0.007 (0.051)	−0.008 (0.053)
EVA	0.140** (0.062)	0.143** (0.055)	0.154*** (0.056)	0.134** (0.056)	0.116** (0.055)	0.134** (0.056)
AWA	0.164** (0.076)	0.160** (0.068)	0.163** (0.069)	0.170** (0.069)	0.153** (0.067)	0.183*** (0.069)
FLO	−0.032 (0.061)	−0.034 (0.054)	−0.039 (0.055)	−0.032 (0.055)	−0.032 (0.053)	−0.034 (0.055)
CUL	−0.019 (0.084)	−0.001 (0.076)	−0.009 (0.076)	−0.017 (0.076)	−0.009 (0.074)	−0.015 (0.076)
SER	0.002 (0.071)	−0.01 (0.064)	−0.012 (0.064)	−0.019 (0.064)	−0.018 (0.062)	−0.020 (0.065)
ADM	0.153 (0.097)	0.153* (0.086)	0.142 (0.087)	0.145* (0.087)	0.137 (0.084)	0.149* (0.087)
INN	0.044 (0.103)	0.081 (0.092)	0.086 (0.093)	0.098 (0.093)	0.097 (0.090)	0.098 (0.093)
RD	0.060 (0.106)	0.056 (0.094)	0.058 (0.095)	0.077 (0.095)	0.064 (0.092)	0.083 (0.095)
control variable	containment	containment	containment	containment	containment	containment
$R^2$	0.432	0.539	0.559	0.563	0.563	0.553
Logl	—	−401.19	−404.04	−405.21	−409.23	−405.56
<i>N</i>	403	403	403	403	403	403

Note: The values in brackets are standard errors. \* $p < 0.1$ , \*\* $p < 0.05$ , \*\*\* $p < 0.01$ .