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Geography of Talent in China During 2000–2015: An Eigenvector Spatial Filtering Negative Binomial Approach

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Abstract: The increase in China's skilled labor force has drawn much attention from policymakers, national and international firms and media. Understanding how educated talent locates and re-locates across the country can guide future policy discussions of equality, firm localization and service allocation. Prior studies have tended to adopt a static cross-national approach providing valuable insights into the relative importance of economic and amenity differentials driving the distribution of talent in China. Yet, few adopt longitudinal analysis to examine the temporal dynamics in the stregnth of existing associations. Recently released official statistical data now enables space-time analysis of the geographic distribution of talent and its determinants in China. Using four-year city-level data from national population censuses and 1% population sample surveys conducted every five years between 2000 and 2015, we examine the spatial patterns of talent across Chinese cities and their underpinning drivers evolve over time. Results reveal that the spatial distribution of talent in China is persistently unequal and spatially concentrated between 2000 and 2015. It also shows gradually strengthened and significantly positive spatial autocorrelation in the distribution of talent. An eigenvector spatial filtering negative binomial panel is employed to model the spatial determinants of talent distribution. Results indicate the influences of both economic opportunities and urban amenities, particularly urban public services and greening rate, on the distribution of talent. These results highlight that urban economic- and amenity-related factors have simultaneously driven China's talent's settlement patterns over the first fifteen years of the 21st century.

Keywords: talent distribution; determinants; eigenvector spatial filtering; panel data analysis; China

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1 Introduction

Human capital accumulation has been recognized as a vital driving force in the development of knowledge-based economies (Lucas, 1988). As a result, policymakers have been universally concerned with ways of attracting and retaining human talent (Florida, 2002; Faggian et al., 2016; 2017). In China, the share of the highly educated population in the labor force has rapidly increased during 2000–2015 (Gu et al., 2019a). The 2015 national 1% population sample survey reported that 170.93 million Chinese citizens held a college degree or above (National Bureau of Statistics of China, 2016), an increase of 72.4% from the same sample collected in 2000. The rise of skilled individuals in China's labor force has drawn much attention from policy-

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makers, employers, and the media. China's government has placed increasing emphasis on enlarging the national pool of highly skilled laborers. It developed the 'National Medium and Long-Term Talent Development Plan (2010–2020)' in 2010 (State Council of China, 2010). This plan states that China needs to transition from labor-intensive to talent-intensive economic activities to increase its competitiveness in the global economy. Similarly, the report of the 19th National Congress of China in 2017 pointed out that China should firmly implement the 'Strategy of Reinvigorating China through Human Resource Development'. It also states that China should cultivate a large number of strategic talent, leading talent in the fields of science and technology, young talent, and highly innovative teams with international standards. Since the 2010s, local governments at all levels have been engaged in the competition for skilled workers on the global stage, implementing policies to attract and retain talent, such as the 'Peacock Plan' in Shenzhen (Shenzhen Municipal Government, 2019). These policies include housing allowances, fast-track *hukou* transfers, and lower thresholds for bank loan applications.

There has been a surge in the number of studies on the migration and redistribution of various kinds of talent in China over the past decade (Qian, 2010; Florida et al., 2012; Liu and Shen, 2014; Liu et al., 2017; Liu and Xu, 2017; Nie and Liu, 2018; Gu et al., 2019a; Zeng et al., 2019; Deng et al., 2020). Due to data availability, prior studies have tended to adopt a static cross-national approach providing novel insights into the relative importance of economic and amenity differentials driving the migration patterns of talent. Yet, changes in the influence of these factors on shaping shifts in the spatial dynamics of migration over time remain underexplored. Additionally, the geographical scale of existing studies has been relatively coarse (i.e., provincial level), restricting our understanding of the location of talent across the urban-rural continuum within and between provinces. Moreover, prior empirical studies tend to focused on understanding the migration and redistribution patterns of highly educated talent during the period pre-2010. Yet less is known about the contemporary patterns of Chinese highly educated talent post-2010. The availability of the 2010 population census (National Bureau of Statistics of China, 2011) and 1% national population sample survey data from 2015 (National Bureau of Statistics of China, 2016) enables investigating more recent spatial patterns of talent in China and identifying their key drivers.

More generally, while previous analysis on migration in Europe has identified a pattern of highly significant spatial autocorrelation in the distribution of talent (Miguélez et al., 2010; Rodríguez-Pose and Tselios, 2011), little has been done to model these spatial effects in a regression framework explicitly. It is shown that talent stock in a particular region may be positively related to the pool of talent in its surrounding areas, which leads to spatial autocorrelation. Researchers have discussed the sources for the spatial autocorrelation: they observed that talent gathered in nearby regions for lower communication cost, knowledge spillover, and sharing public resources (Miguélez et al., 2010). Interregional frequent mobility of talent between neighboring areas may also lead to positive spatial autocorrelation in talent stocks (Liu and Shen, 2017), which may also result from close cross-regional social talent networks (Gu et al., 2019a). A handful of studies have used autocorrelation analysis to investigate the distribution of talent within a country or a region (Song et al., 2016; Nie and Liu, 2018). Yet little research has taken into account the presence of spatial dependence when assessing the geographic distribution of talent within countries. Without proper treatment, latent spatial autocorrelation may lead to estimation bias in regression models. Eigenvector spatial filtering (ESF) is a technique for capturing latent spatial autocorrelation in model residuals (Liu and Shen, 2017; Gu et al., 2019b). Each eigenvector extracted from a spatial weight matrix can be considered as a control variable for spatial autocorrelation. Hence, incorporating eigenvectors into regression models can help to reduce the effect of spatial autocorrelation, thus reduce model bias and enhancing model fitting (Griffith, 2003; Chun and Griffith, 2011).

To tackle any estimation bias arising due to spatial autocorrelation (Griffith, 2003), this research builds an eigenvector spatial filtering negative binomial panel model (ESF-NBPM) and examines the determinants of talent in China at the city level from 2010 to 2015 (Gu et al., 2019b). The contribution of this article is threefold. First, we analyzed the spatial patterns of talent in China at a finer geographical resolution (i.e., the city-level), compared to previous analysis based on provincial-level data. Our more detailed geographic analysis will contribute to the literature on the migration patterns of Chinese talent by developing an understanding of the intra-provincial differences in the locational choices of talent and providing more accurate identification of the key underpinning factors of these choices. Second, our analysis also contributes to our understanding of changes in the relative importance of local factors shaping the distribution of talent over time. Third, we applied the ESF specification to tackle spatial autocorrelation moving away from traditional gravity models which omit the spatial interconnectivity in the distribution of talent stocks.

The goal of the article is to investigate the spatial-temporal patterns of talent in China between 2000 and 2015. It first reviews the existing literature on spatial patterns and determinants of talent, followed by the descriptions of data sources and research methods. Then, the article assesses the spatial concentration or evenness in the spatial distribution of talent in China and analyses its evolution over time based on a range of inequality measures. Finally, an ESF-NBPM is built to identify the key driving factors of the spatial distribution of talent before discussing the policy implications from our findings and then providing some final concluding remarks.

2 Literature Review

2.1 Determinants of geographic distribution of talent

Economic theories have made considerable efforts to identify the factors shaping the spatial distribution and redistribution of talent (Lewis, 1954; Sjaastad, 1962; Todaro, 1969). New classical theory assumes migration and redistribution as the resulting process of individuals thinking rationally and independently, aiming to maximize their utility. Empirical results evidence that differentials in regional economic opportunities are dominant factors influencing the spatial distribution of talent (Sjaastad, 1962; Todaro, 1969). The skilled labor force is spatially focused and thus reinforcing agglomeration economics (Harris and Todaro, 1970). Research has shown that highly skilled and educated migrants tend to move to regions with high-income levels and abundant job opportunities (Arntz, 2010; Scott, 2010; Rowe et al. 2013; Liu and Shen, 2014; Tang et al, 2014). Employment stability also plays an important role in attracting skilled labor (Xu and Ouyang, 2018).

Alternatively, additional theories and models have been developed which emphasize the role that amenity differentials play in the redistribution of talent. They assume that spatial differences in economic opportunities reflect largely compensating differentials related to corresponding spatial differences in amenities (Graves 1976). Based on the principles of Graves' *equilibrium* model, Glaeser et al. (2001), Clark et al. (2002) and Florida (2002) expanded economic-driven migration models to include urban amenities. Empirical research has shown that a strong relationship between regional amenities and redistribution of talent exists, particularly in terms of natural environmental amenities (Knapp and Gravest, 1989; Partridge, 2010), urban public services (Woodward et al., 2006; Rowe et al. 2017), and urban consumer facilities (Glaeser et al., 2001).

The location of universities has emerged as a key urban amenity factor displaying a significant relationship with the distribution of highly educated individuals (Rowe, 2013). Universities are key producers of talent. In less-attractive and underdeveloped regions, universities may also play the role of 'talent exporters' since local highly educated graduates tend to move to other regions for employment (Tang et al., 2014). When talent is less mobile and has a higher settlement intention of the region, universities have a more notable effect on the pool of local talent (Qian, 2010).

2.2 Spatial determinants of talent in China

There has been a recent surge in the number of studies examining the spatial patterns of talent in China and their underpinning factors (Liu and Shen, 2014; Liu and Xu, 2017; Nie and Liu, 2018; Yu et al., 2019; Lao and Gu, 2020). Collectively, these studies revealed an unbalanced spatial distribution at the city or provincial scales (Liu and Shen, 2014; Nie and Liu, 2018). They have also demonstrated the critical role of economic factors influencing the mobility decisions of a range of different types of talent labor, including highly skilled individuals (Liu and Shen, 2014) and scientists. They have shown that economic factors including GDP, average wage, unemployment rate, and industrial structure comprise the fundamental forces shaping the spatial distribution of China's population and talent (Liu and Shen, 2014; Yu et al., 2019). They have also indicated that the uneven distribution of talent has been the result of a pronounced gap between developed and undeveloped regions in terms of economic development and living conditions (Liu and Shen, 2014). Furthermore, the siphoning effects of talent spurring economic development in major cities may negatively impact small and medium-sized settlements, reinforcing spatial economic inequalities.

Consistent with Graves (1976) and Glaeser (2001), scholars have explored the role of amenities in influencing the distribution of talent in China (Liu and Shen, 2014). Evidence indicates that public services, such as education and medical care represent a necessary condition to attract talent (Liu and Shen, 2014; Song et al., 2016). The local share of talent is also correlated with the local quality of the living and consumption facilities, including leisure and entertainment infrastructure, public safety, and shopping options. With the improvement of urban and inter-regional transportation infrastructure in China, regional traffic accessibility is also found to be positively associated with the distribution of talent (Gu et al., 2019a).

Scholars have recently compared the impact of economic opportunities *versus* amenities on the mobility patterns of talent in China. The cumulative evidence thus far suggests that economic opportunities tend to prevail over amenity-driven migration (Liu and Shen, 2014; Gu et al., 2019a; Yu et al., 2019). However, most prior empirical analyses have adopted a cross-sectional perspective on the distribution of talent, neglecting the temporal dynamics of this process. China has continued to experience sustained economic growth in the last decade with focused investment in eastern and south-eastern areas of the country (Breznitz and Murphree, 2011). These concentrated poles of economic development are likely to have enticed large flows of talent, generating losses elsewhere.

2.3 Application of spatial modeling approach in population studies

Spatial autocorrelation is an inherent property in human migration and geographic data. Prior work has consistently shown the presence of strong and positive spatial autocorrelation in the spatial distribution of talent in China (Li et al., 2012; Gu et al., 2019a). Six potential mechanisms that may lead to patterns of spatial autocorrelation have been identified. First, the spatial concentration of talent in an area has been found to lead to a reduction in communication cost of talent in neighboring regions. Second, it may also lead to an increase in talent volumes in neighboring regions, to take advantage of the existence of agglomeration economies (Miguélez et al., 2010). Third, regional economic growth trigger talent surge as a result of a knowledge spillover effect from adjacent cities with a large stock of talent and technology innovation enterprises (Henderson, 2007). Fourth, mobility of talent searching for jobs and residence tends to be spatially focused around their current region of residence and neighboring regions (Liu and Shen, 2017). Fifth, factors influencing the location of talent in a particular region spills over to nearby areas (Miguélez et al., 2010). Sixth, the inter-regional social network of talent reinforces concentration around local areas (Gu et al., 2019a). We recognize all these mechanisms producing spatial autocorrelation may result from the modifiable areal unit problem (MAUP) as often data used for spatial analysis are based on arbitrary administrative boundaries (Chi and Zhu, 2008; Casado et al., 2017; Rowe, 2017).

When modeling the process of the distribution of talent, traditional econometric models assume independent and identically distributed (i.i.d.) in the model residuals. Without controlling the effect of spatially structured random component (i.e., spatial autocorrelation), model residuals may contain significant spatial autocorrelation, thus violating the i.i.d. assumption and leading to endogeneity (Griffith, 2003; Gu et al., 2019b). Therefore, appropriate methods should be applied to reduce model bias resulting from spatial autocorrelation, such as the autoregressive model (Anselin, 1988) and the Getis filtering approach (Getis and Griffith, 2002). By adding the selected eigenvectors of the spatial weight matrix as the proxies for spatial autocorrelation, eigenvector spatial filtering (ESF) is another approach for tackling spatial autocorrelation in data. Comparing to other approaches for filtering spatial autocorrelation, ESF is easier to implement for various types of models and does not change the estimation method of the model. Thus it is more flexible and has fewer restrictions when capturing spatial autocorrelation (Griffith, 2003).

3 Data and Methods

3.1 Study area

Our research area includes 31 provinces in China, except for Hong Kong, Macao, and Taiwan. City extents comprise our geographic unit of analysis because they typically represent the spatial scale at which policies are formulated for the attraction and retention of talent, and factors influencing talent often vary significantly across cities (Nie and Liu, 2018; Gu et al., 2019a). Based on individual-level records from population censuses and sample surveys, the stock of talent (i.e., the raw number of highly educated people) is aggregated to the city level. A total of 309 cities are chosen for our basic dataset. Cities in China include prefecture cities and autonomous prefectures. When we did regression analysis, we excluded data on autonomous prefectures because of their poor quality and number of missing entries. Then, we eliminate samples of missing data and with no neighboring city. Finally, we used a total of 233 cities out of 309 units for regressions. The selected 233 cities were representative since they covered cities of different sizes, administrative levels, and geographical regions. China's economic geography is divided into four economic-geography regions: the Eastern, Central, Western, and Northeastern regions (Fig. 1) (Zhou et al., 2019).

3.2 Methodologies

3.2.1 Concentration index (CI)

FollowingYang et al. (2014), we used the concentration index (CI) method to describe the spatial concentration of talent across cities. The concentration index can be expressed in terms of the proportion (%) of talent in 1% of a country's land area. It is represented as:

$$CI_i = \frac{P_i/P_n \times 100\%}{A_i/A_n \times 100\%} = \frac{P_i/A_i}{P_n/A_n} \tag{1}$$

where CI_i denotes the concentration index of city i; P_i is the talent stock of city i; A_i is the land area of city i; A_n is the total land area of China; P_n is China's total stock of talent.

3.2.2 Moran's I

Measuring the degree of spatial autocorrelation is vital for the understanding of the distribution of talent in China. Moran's I is one of the most widely used methods for spatial dependence of geographical attributes between neighboring regions (Zhou et al., 2019). The formula of the Moran's I is:

$$I = (X'WX)/(X'X) \tag{2}$$

where I is the Moran's I for the density of talent of cities. X denotes the vector of observations, X' is the transpose of X, and W is the standardized spatial weight matrix under *queen* criteria. The *queen* spatial weight matrix has been widely applied in defining the spatial relationship of China's cities (Hong and Sun, 2011; Gu et al., 2019a). The value of Moran's I ranges from –1 to 1, with positive values for positive spatial autocorrelation and negative values for negative spatial autocorrelation.

3.2.3 Coefficient of variation (CV)

Coefficient of variation (CV) can measure the degree of differences in the distribution of talent of cities. CV is calculated as follows:

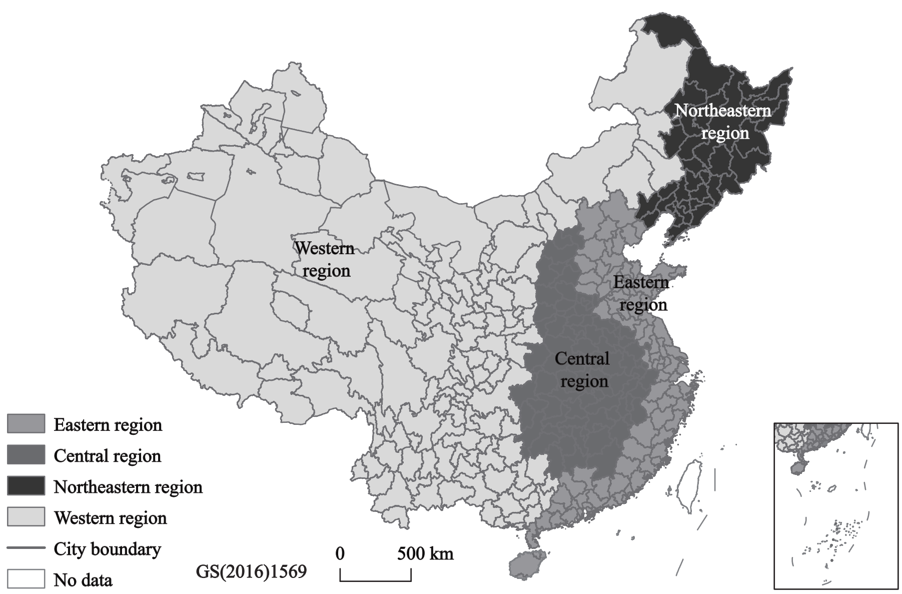

Fig. 1 Four economic geography regions in China. Hong Kong, Macao and Taiwan of China are not included

$$CV = \frac{1}{\overline{P}}\sqrt{\frac{\sum_{i=1}^{n}(P_i-\overline{P})^2}{n-1}} \tag{3}$$

where CV is the value of the coefficient of variation. $\overline{P}$ denotes the average stock of talent across cities; n is the number of cities.

3.2.4 Econometric model

To model migration flows and identify the patterns underpinning their key drivers, we use a negative binomial model (NBM) framework which is appropriate to model count data with overdispersion (Cameron and Trivedi, 2013): our dependent variables are counts of talent, i.e., number of people with a college degree or above. The NBM introduces a parameter α that measures overdispersion in the data. For our dependent variables, the variance was significantly larger than the mean, so that we applied a fixed-effects overdispersion NBPM proposed by Hausman et al. (1984) to model panel data taking the density of:

$$Pr(y_{it}|\mu_{it},\alpha) = \frac{\Gamma\left(\alpha^{-1}+y_{it}\right)}{\Gamma(\alpha^{-1})\Gamma(y_{it}+1)}\left(\frac{\alpha^{-1}}{\alpha^{-1}+\mu_{it}}\right)^{\alpha^{-1}}\left(\frac{\mu_{it}}{\alpha^{-1}+\mu_{it}}\right)^{y_{it}} \tag{4}$$

$$E(y_{it}|x_{it}) = \mu_{it} = \exp(x_{it}'\beta) \tag{5}$$

where Γ is the Gamma integral; μ_{it} equals $E(y_{it}|x_{it})$; α is the dispersion parameter of the Gamma distribution. When this parameter tends to 0, the NBM becomes a Poisson Model; y_{it} represents the talent stock of city i at time t; x_{it} represents a vector of independent variables of the city i at time t; β represents the vector of estimates capturing the relationship between the independent and dependent variables. The model also incorporates a parameter for individual-specific fixed effects (Cameron and Trivedi, 2013).

To correct for spatial autocorrelation in our regression estimates, we use eigenvector spatial filtering (*ESF*). ESF is implemented as follows: first, we constructed an n-by-n binary spatial weight matrix W under *queen* criteria using GeoDa to represent the connectivity of Chinese cities (n denotes the total number of cites). The second step is to construct a transformed spatial weight matrix. Given a matrix $M = I–AA'/n$, where I is an n-by-n identity matrix, and A is an n-by-1 vector of 1s. M can center the spatial weight matrix W by MWM. Third, we calculated the eigenvalues and eigenvectors of the matrix MWM:

$$MWM = E\Lambda E' \tag{6}$$

where E is the matrix of eigenvectors decomposed by the transformed matrix, and Λ is a diagonal matrix with corresponding eigenvalues.

Getis and Griffith (2002) demonstrated that the eigenvectors in the ESF method are orthogonal and uncorrelated, and each eigenvector corresponds to a unique pattern of spatial autocorrelation. Additionally, each individual eigenvector in E can be linked to a Moran's I:

$$I_j = \frac{n}{A'WA}\frac{e_j{}'MWMe_j}{e_j{}'Me_j} \tag{7}$$

where n is the number of cities. I_j is the Moran's I for the jth eigenvector e_j. Griffith (2003) suggested identifying with a critical value of the corresponding eigenvalues indicating a specific minimum spatial autocorrelation level (e.g., Moran's I = 0.25). After the selection of the candidate eigenvectors, a subset of eigenvectors can be chosen with the Akaike information criterion (AIC, Chun, 2011). This process minimizes the estimation error without reducing too much the degree of freedom of the model.

For space-time panel data analysis (e.g., the NBPM), eigenvectors need to be concatenated T times to match the total number of space-time observations (Chun, 2011). Because the spatial structure of the data is invariant over time, linear mixed models (LMM) and generalized linear mixed models (GLMM) are suggested to apply to account for spatial and temporal autocorrelation with ESF technique (Chun, 2011; 2014). Fortunately, the fixed effects NBPM specification proposed by Hausman et al. (1984) can accommodate the time-invariant spatial autocorrelation represented by the selected eigenvectors (Gu et al., 2019b). After adding eigenvectors that are used to control the effect of spatial autocorrelation, our model specification can be defined by:

$$E(y_{it}|x_{it},e_{it}) = \mu_{it} = \exp(x_{it}'\beta + e_{it}'\gamma) \tag{8}$$

where e_{it} denotes the selected eigenvectors of city i at time t, and γ is the vector of estimators.

3.3 Data

Following existing studies (Liu and Shen, 2014; Nie and Liu, 2018; Gu et al., 2019a; 2020a; Qi et al., 2020), we defined talent: individuals with a college degree or above. The rationale of using academic qualifications to define talent is that academic qualifications provide an accurate representation of human capital embedded in the labor force. In most cases, regional development policies of cities often use academic qualifications to define and divide talent (Rowe 2013).

We used data from the National Bureau of Statistics of China (2001; 2006; 2011; 2016). The data extracted from the surveys conducted every five years between 2000 and 2015 can support a four-year panel data analysis. In 2000, there were 45.6 million highly educated individuals in China, comprising 3.67% of the total population. By 2005, this number had increased by 30 million to comprise 75.7 million, and by 74 million to represent 120.1 million in 2010. In 2015, the pool of Chinese talent comprised 151.1 million and accounted for 10.99% of the total population. For the independent variables, we used to explain the spatial distribution of talent in China. We draw on data from 1999, 2004, 2009, and 2014 reported by the National Bureau of Statistics of China (2000; 2005; 2010; 2015). As in previous studies (Liu and Shen, 2014; Gu et al., 2019a), we included independent variables to capture two broad sets of factors: economic and amenity factors, and also introduced a range of control variables. Three variables were used to capture differences in economic opportunities across cities: gross domestic product (GDP), the average number of urban employed staff and workers per 10 000 habitants (EMPLOY), and the proportion of tertiary industry output in GDP (INDUS). Expectedly, a higher level of GDP and a larger number of urban employees per 10 000 provides adequate and diverse job opportunities for the region, which may attract more talent to settle in (Nie and Liu, 2018). A higher rate of tertiary industry outputs in GDP means a more optimized industrial structure, which may also conduce the stock of talent (Gu et al., 2019a).

Four variables were used to capture differences in public sector amenities: including the ratio of total expenditure on science, technology and education in total fiscal expenditure (STEEXPEND), the ratio of fiscal expenditure to revenue (SPEND), the number of primary school teachers per 10 000 students (PRIEDU) and the number of doctors per 10 000 people (MEDICAL). Expectedly, better provision of public services will increase the stock of talent (Glaeser et al., 2001). We also included two variables to account for differences in natural amenities: green coverage rate (GERRN), and sulfur dioxide emissions (SO_2). Research has also shown the vital role of natural amenities in the decision-making of talent (Knapp and Gravest, 1989; Partridge, 2010).

Additionally, we introduced four other control variables which may help to explain the distribution of talent: the number of college students per 10 000 habitants (UNISTU), population sizes of the city (POP), per capita fixed-asset investment (FAI), and population density (DENS). The dependent variable of the study is the raw number of talent, thus it is essential to control the effect of the population size as well as the economic density and agglomeration effect. The number of college students per 10 000 habitants was used to control the supply of talent, and FAI was considered as the proxy for urban construction investment. A description of variables is provided in Table 1.

4 Results and Analyses

4.1 Distribution of talent in China

This section determines the extent of spatial concentration of talent across cities in China. We divided 309 cities into three types of areas based on their CI score: intensively-distributed areas (CI $\geq$ 2), evenly-distributed areas (0.5 < CI < 2), and sparsely-distributed areas (CI $\leq$ 0.5). We analyzed the distribution of talent across these areas and the results are reported in Table 2. We found that talent tended to concentrate on a small number of intensively-distributed areas with an increasing density from 32.28 persons/km^2 in 2000 to 99.97 persons/km^2 in 2015. Just over 10% of China's land area clustered about 70% of the highly educated population during the 2000–2015 period.

Most of the highly educated population has tended to concentrate in large urban agglomerations and provincial capitals, particularly in the eastern coastal region of the country (Fig. 2). This region encompasses intensively-distributed, economically developed areas, including first-tier cities such as Beijing and Shanghai, capital cities in the central and eastern regions such as Zhengzhou, Taiyuan, Wuhan, and Nanjing, and the cities in Pearl River Delta urban agglomerations such as Dongguan, Zhuhai and Zhongshan.

Evenly-distributed areas were mainly located in the central-eastern areas of China and have seen a fluctuation in the share of the highly educated population,

Table 1 Description and expected effects of variables

Type	Variable	Description	Expected effect	Number	Mean
Dependent variables	TALENT	Number of people with a college degree or above of each city in 2000, 2005, 2010, 2015		932	359602.1577
Economic opportunity variables	GDP	Gross GDP of each city in 1999, 2004, 2009 and 2014 / (10000 yuan (RMB))	+	932	15.6558
	EMPLOY	Average number of urban employed staff and workers per 10000 habitants in 1999, 2004, 2009, and 2014	+	927	6.8535
	INDUS	The proportion of tertiary industry to GDP of each city in 1999, 2004, 2009 and 2014 / %	+	931	36.4876
Amenity variables	STEEXPEND	The proportion of per capita science, technology and education expenditure to the financial expenditure of each city in 1999, 2004, 2009 and 2014 / %	+	932	18.1333
	SPEND	The ratio of per capita financial expenditure to per capita fiscal revenue of each city in 1999, 2004, 2009 and 2014 / %	+	932	214.6244
	PRIEDU	Number of primary school teachers per 10000 primary school students of each city in 1999, 2004, 2009 and 2014	+	931	6.2942
	GREEN	Greening rate of each city in 1999, 2004, 2009 and 2014 / %	+	929	35.2725
	SO_2	Emissions of industrial sulfur dioxide of each city in 1999, 2004, 2009 and 2014 / t	–	924	8.6791
	MEDICAL	Number of doctors per 10000 people of each city in 1999, 2004, 2009 and 2014	+	932	2.8203
Control variables	UNISTU	Number of college students per 10000 people of each city in 1999, 2004, 2009, and 2014	+	932	3.6455
	POP	Population sizes of each city in 1999, 2004, 2009, and 2014 / (10000 persons)	+	932	5.8624
	FAI	Per capita fixed assets investment of each city in 1999, 2004, 2009 and 2014 / (10000 yuan (RMB))	NS	931	8.9678
	DENS	Population density of each city in 1999, 2004, 2009 and 2014 / (persons/km^2)	+	916	6.4728

Notes: '+' denotes a positive expected effect, '–' denotes a negative expected effect, 'NS' represents an unsure expected effect; All independent variables are in natural logarithm expect for INDUS, STEEXPEND, SPEND, and GREEN

Table 2 Distribution characteristics of talent from 2000 to 2015

Area	Talent proportion / %				Land proportion / %				Density / (persons/km^2)			
	2000	2005	2010	2015	2000	2005	2010	2015	2000	2005	2010	2015
Intensively-distributed area	66.96	66.59	70.65	65.16	11.60	12.09	12.30	11.67	32.38	46.03	85.09	99.97
Evenly-distributed area	28.03	27.16	23.40	28.84	26.36	25.94	23.64	27.94	5.97	8.75	14.67	18.48
Sparsely-distributed area	5.01	6.25	5.28	6.00	62.03	61.97	64.06	60.39	0.45	0.84	1.22	1.78

with a slight rise in 2015. Yet, these areas displayed a significant increase in the density of talent. Sparsely-distributed areas emerged persistently in western and north-west parts of the country. They occupied the majority of the land area (more than 60%) but have consistently contained only less than 6% of China's highly educated population though they recorded a small increase in density reflecting a reduction in land area.

We also mapped the Hu line and found that the majority of intensively and evenly-distributed areas were located in the southeast of the Hu line (Hu, 1935). Averagely, 94.7% of China's highly educated population was distributed in the southeast of the Hu line (covered 44.1% of the country's total land areas) between 2000 and 2015. Yet, the northwest region only had 5.2% of the highly educated population and 55.9% land areas. This finding was consistent with the research on the Hu line's segregation on the distribution of China's total population (Wang et al., 2019).

Besides, significant spatial autocorrelation was detected in talent distribution. We computed the Moran's I for the density of talent of cities between 2000 and 2015 in China and observed that this value has increased from 0.030 ($P < 0.05$) in 2000 to 0.073 ($P < 0.001$) in 2015.

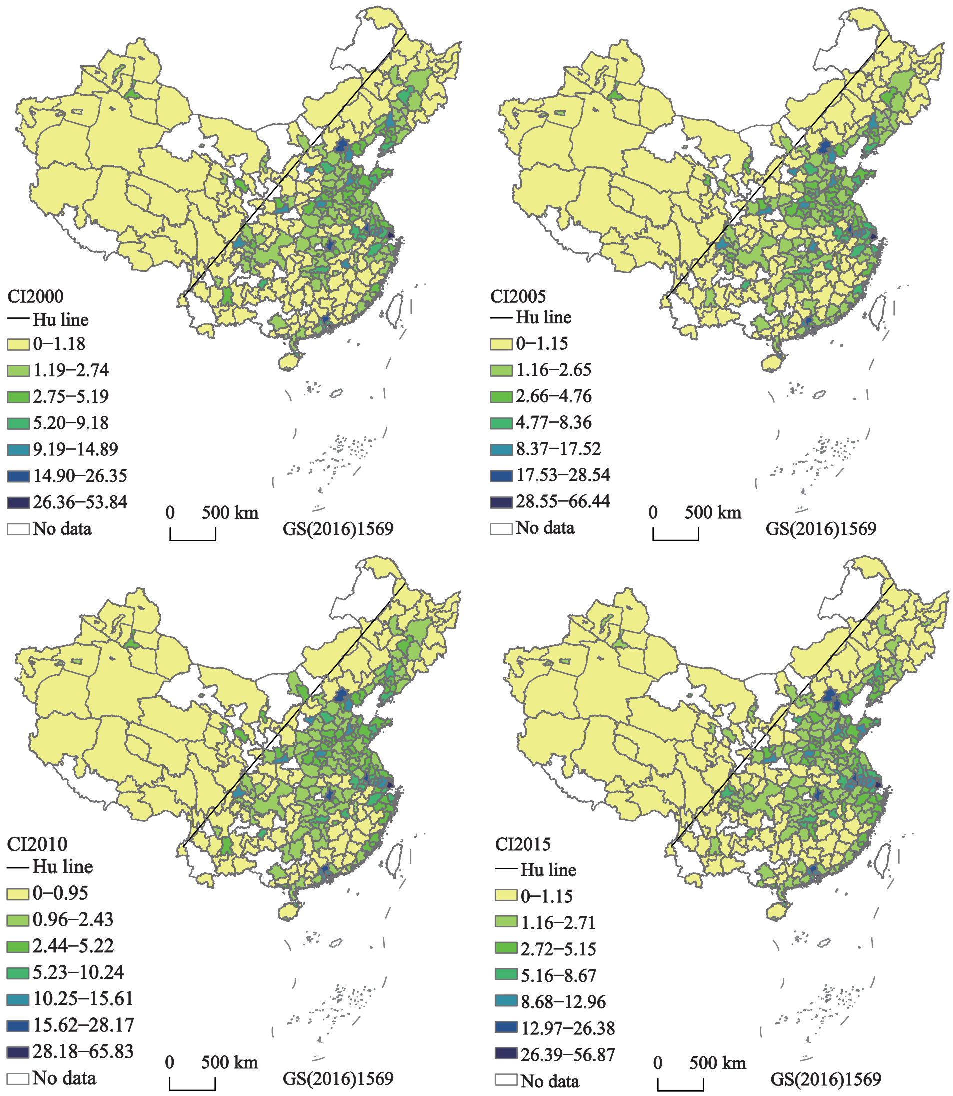

Fig. 2 The concentration index of spatial patterns of talent at the city-level of China, 2000–2015. Hong Kong, Macao and Taiwan of China are not included

This indicated that the density of talent of a city was closely related to that of its nearby cities and that this spatial dependence degree has strengthened over time. Also, the distribution of talent showed spatial inequality. The *CV* is 1.855 in 2000 to 2.073 in 2005 and down to 1.862 in 2015, indicating a persistent pattern of high spatial concentration in the density of highly educated population across cities, with little variation over time. The increasing uneven trend in the first ten years was closely related to a significant difference in college enrollment expansion in particular cities, including first-tier cities (e.g., Beijing and Shanghai) and provincial capitals (e.g., Wuhan and Chengdu) after the introduction of the proposed the 'Action Plan for Education Revitalization in the 21st Century'. This plan has resulted in a variation in the local supply of educated people across cities. The slight decrease in the concentration of talent between 2010 and 2015 may reflect recent national initiatives of regional development to reduce spatial inequalities (e.g., the 'National Medium- and Long-Term Talent Development Plan (2010–2020)' and the 'National New-Type Urbanization Plan (2014–2020)'.

Underpinning this national pattern of spatial concentration, stark regional differences in the distribution of talent exists. To explore this, we obtained the average density of talent in China's four economic-geography regions from 2000 to 2015 (Fig. 3). The eastern region consistently recorded the highest density of talent, displaying a significant increase from 20 persons/km^2 in 2000 to over 70 persons/km^2 in 2015. The western re-

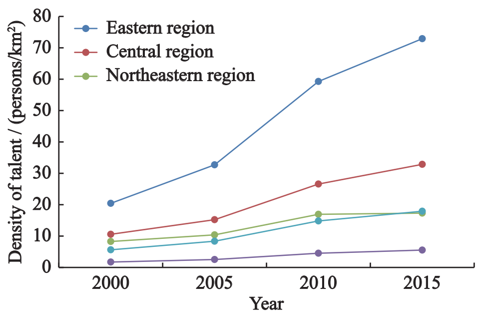

Fig. 3 Density of talent in each economic-geography region and the whole of China from 2000 to 2015. Hong Kong, Macao and Taiwan of China are not included

gion reported the lowest and most marginal density level remaining below 10 people/km^2 since 2000. The results further showed that after the implementation of the 'China Western Development' in 1999, a larger proportion of talent moved away from the central, northeastern, and western parts of China to the eastern part, and this trend has been more evident over time.

4.2 Determinants of talent distribution

4.2.1 Model processing

To control time-fixed effects, we constructed three time dummy variables in all the models. We tested for strict multi-collinearity of models with the VIF test under the specification of pooled ordinary least squares (OLS). The VIF values of each variable were all less than 4, indicating that there was no strict multi-collinearity problem. We also calculated the covariance matrix for all variables and found that the pair-wise correlation coefficients did not exceed 0.7. Furthermore, including time-lagged independent variables in our models helps reducing potential endogeneity caused by reverse causation. Additionally, the use of ESF effectively reduces the effect of spatial autocorrelation in residuals and further alleviates any potential endogeneity (Getis and Griffith, 2002; Gu et al., 2019b).

To test for spatial autocorrelation, we calculated a panel-type standardized Moran's I for talent stock in 233 cities during 2000–2015. The Moran's I for this test was 0.125 ($P < 0.01$), indicating statistically significant and positive spatial autocorrelation in the spatial pattern of talent in cities. To reduce the effect of the spatial autocorrelation, it would be good to employ the ESF specification to perform our regression analysis. All models in the study were constructed under the specification of the NBPM. The model results are reported in Table 3. Model 1 only includes three economic variables while Model 2 includes six amenity variables. Model 3 incorporates economic and amenity variables together, followed by a more general model (Model 4) considering all the control variables. Model 5 is an ESF NBPM, where selected eigenvectors are added to control the effect of the autocorrelation. Ultimately, the results of Model 6 using the bootstrap standard errors serve as the robustness check of our main findings.

4.2.2 Model results

This section begins with the results of each model. Results from Model 1 showed statistically significant coefficients of GDP (GDP) and average urban employed staff and workers per 10 000 habitants (EMPLOY), indicating the positive impacts of economic development level and job opportunities. However, the coefficient of INDUS was insignificant. Results from Model 2 revealed significant coefficients for scientific technology and education expenditure proportion (STEEXPEND), the number of primary school teachers per 10 000 students (PRIEDU), and regional greening rate (GREEN), indicating the roles of urban public services and natural comforts in driving the distribution of talent. However, SPEND and SO_2 seemed to have no relationship with the stock of talent. This was in part because the expenditure-income ratio represents both the ability of public services and the local financial burden, which may lead to an ambiguous effect. Likewise, emissions of industrial sulfur dioxide can measure both environmental pollution and local economic level to some degree. Also, we found that the effect of local medical services was insignificant.

Results from Model 3 showed similar magnitudes of coefficients for economic-related variables and amenity variables as Models 1 and 2, which, to some extent, verified the robustness of the impact of the twofold factors on local talent stock. After we controlled the economic variables, the effect of SO_2 was still insignificant, implying that Chinese talent did not consider air pollution when they decided whether to settle in. Also, they would not take medical services into account.

Model 4 entered four control variables but presented very similar results for economic variables and amenity variables as Models 1–3, despite minor changes in their coefficients and significance. In line with our expectations, the number of college students per 10 000 people (UNISTU), and the local population scale (POP) were

Table 3 Results from the negative binomial panel models and eigenvector spatial filtering negative binomial panel models

Variables	(1) NBPM TALENT	(2) NBPM TALENT	(3) NBPM TALENT	(4) NBPM TALENT	(5) ESF NBPM TALENT	(6) ESF NBPM TALENT
GDP	0.2547***		0.2487***	0.0975***	0.1345**	0.1345*
	(0.0422)		(0.0430)	(0.0588)	(0.0582)	(0.0837)
EMPLOY	0.0654*		0.0952**	0.1809***	0.1726***	0.1726***
	(0.0391)		(0.0442)	(0.0476)	(0.0486)	(0.0650)
INDUS	0.0006		–0.0009	–0.0036	–0.0025	–0.0025
	(0.0021)		(0.0022)	(0.0024)	(0.0023)	(0.0026)
STEEXPEND		0.0107***	0.0113***	0.0065**	0.0061**	0.0061**
		(0.0030)	(0.0030)	(0.0031)	(0.0031)	(0.0028)
SPEND		–0.0002	–0.0001	–0.0001	–0.0001	–0.0001
		(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)
PRIEDU		0.1341**	0.1729***	0.1795***	0.1931***	0.1931**
		(0.0641)	(0.0652)	(0.0629)	(0.0619)	(0.0778)
GREEN		0.0026***	0.0026***	0.0029***	0.0028***	0.0028***
		(0.0006)	(0.0006)	(0.0006)	(0.0006)	(0.0009)
SO_2		0.0192	0.0090	0.0035	0.0057	0.0057
		(0.0128)	(0.0126)	(0.0035)	(0.0127)	(0.0123)
MEDICAL		–0.0345	–0.0546	–0.0333	–0.0501	–0.0501
		(0.0494)	(0.0521)	(0.0512)	(0.0515)	(0.0631)
UNISTU				0.0124*	0.0138**	0.0138**
				(0.0060)	(0.0062)	(0.0058)
POP				0.4222***	0.3603***	0.3603***
				(0.0922)	(0.0916)	(0.1168)
FAI				–0.0016	0.0007	0.0007
				(0.0314)	(0.0317)	(0.0373)
DENS				–0.0287	–0.0344	–0.0344
				(0.0241)	(0.0234)	(0.0244)
year2005	0.2242***	0.1393	0.0639	0.1717	0.1260	0.1260
	(0.0388)	(0.1112)	(0.1110)	(0.1274)	(0.1249)	(0.1359)
year2010	0.5735***	0.6362***	0.3745***	0.6162***	0.5449***	0.5449***
	(0.0619)	(0.1142)	(0.1233)	(0.1454)	(0.1437)	(0.1703)
year2015	0.6587***	0.9533***	0.4807***	0.7406***	0.6459***	0.6459***
	(0.0941)	(0.1125)	(0.1393)	(0.1684)	(0.1669)	(0.2078)
CONSTANT	–1.9983***	1.2035***	–3.1975***	–3.6825***	–3.8318***	–3.8318***
	(0.6704)	(0.4178)	(0.8282)	(0.8451)	(0.8376)	(1.1247)
N	926	921	915	898	898	898
Eigenvectors	no	no	no	no	yes	yes
AIC	16675	16570	16390	15976	15970	15970
Log likelihood	–8330.4301	–8275.0203	–8182.1567	–7970.8279	–7959.6980	–7959.6980

Notes: *** represents $P < 0.01$, ** represents $P < 0.05$, * represents $P < 0.1$; Standard errors are in parentheses for Models 1 to 5, and bootstrap standard errors are in parentheses for Model 6. Meanings of variables see Table 1 positively related to the stock of talent, verifying the impact of talent supply and city size. However, the coefficients of population density (DENS) and per capita fixed assets investment (FAI) were not statistically significant in Model 4.

In Model 5, we further added the selected set of eigenvectors as the proxies for spatial autocorrelation and found that the log-likelihood of the Model 5 increased compared to Model 4, together with a decline in its AIC value. This indicated that the ESF NBPM had a better model fitting, which outperformed the models without eigenvectors. Likewise, both of the individual and time fixed effects were controlled. Results from Model 5 unveiled a significant effect of economic opportunities and amenities on talent distribution. The regional economic development level played a prominent role. GDP reflects higher economic benefits for local communities and population in terms of income and consumption spillover effects, generating further consumption in the local economy as well as job creation. The results indicated that an average of a 1% increase in urban GDP led to a 0.1345% increase in the stock of talent between 2000 and 2015. The role of employment chances was also significant, with a 1% increase in the number of average urban staff and workers per 10 000 resulting in a rise in the local talent stock of 0.1726%. The industrial structure of the local economy did not seem to play an important role in influencing the pool of local talent, which was partly due to the differences in the industrial structure were small across most cities.

Specific urban amenities were also significantly associated with the spatial distribution of talent. In contemporary China, a large percentage of talent tends to migrate with their family and a primary concern is an education for their children (Gu et al., 2020b). The primary education context of destination cities is thus important in attracting talent. Our results showed that if the number of primary school teachers per 10 000 students (PRIEDU) increased by 1%, the pool of talent expanded by 0.1931%. Other urban amenities also played a role but to a lesser extent. The ratio of per capita science, technology, and education expenditure to financial expenditure (STEEXPEND) emerged as a key factor representing the importance placed by the local government on urban technology and education development. Our results indicated that a 1% increase in this ratio resulted in a rise in the stock of talent of the city of 0.0061%. Besides, the rate of urban greening (GREEN) displayed a positive relationship with talent stock. Model 5 suggested that a 1% increase in urban greening rate led to a 0.0023% increase in the talent stock of the city.

Out of our expectation, other amenity variables were insignificant in Model 5, including the proportion of per capita fiscal expenditure to fiscal revenue (SPEND), sulfur dioxide emissions (SO_2), and the number of doctors per 10 000 (MEDICAL), which implied that the relationship between urban amenities and the distribution of talent was not much clear. This might be partly because there were various manners in our model that measured urban amenities. Fortunately, the three significant variables of amenities had a strong relationship between the distribution of talent across the models, which showed the crucial role of amenities, especially for public services and greening rate.

4.2.3 Robustness checks

We observed the robustness of our model results in the following two aspects. First, we adopted a strategy for adding variables by step. We found that key variables of economic opportunities and amenities remained significant when we gradually put control variables and eigenvectors into the model. Also, when only entering economic or amenity variables, the key variables were still significant. This has confirmed the robust relationship between economic opportunities, amenities, and the stock of talent in the city. Beyond that, we constructed a model with a bootstrap technique (resampling 400 times) to compute the robust standard errors (Model 6) and regressed the dependent variable on the same set of variables. The results reported in Table 3 revealed that the impact of economic and amenity variables was still robust. In summary, through econometric analysis, we found that urban GDP, average urban employed staff and workers per 10 000, the ratio of per capita science, technology, and education expenditure, the number of middle school teachers per 10 000 students, and urban greening rate had a robust and critical relationship between talent distribution in Chinese cities during the fifteen years.

5 Discussion

The present study has widened the understanding of China's talent distribution from 2000–2015 by using a four-year city-level data set extracted from population censuses and sample surveys. Regarding underlying spatial autocorrelation, the research has adopted an ESF NBPM, which made it possible to arrive at accurate conclusions and promising policy recommendations. Our findings have suggested a persistently spatial uneven and concentration pattern of talent distribution in China in the first fifteenth years of the 21st century, which echoed the conclusions of previous literature (Nie and Liu, 2018; Gu et al., 2019a). Our econometric analysis has highlighted a significant relationship between the economy of a city and talent stock. The finding was also consistent with the evidence from previous cross-sectional studies examining the spatial distribution of China's skilled workers or highly educated people and their determinants, largely prior to 2010 (e.g., Liu and Shen, 2014). Our work expands previous work by revealing that the systematic key role of economic factors in shaping distribution patterns of talent in China over time.

Not as found in previous cross-sectional studies (Liu and Shen, 2014; Gu et al. 2019a; Yu et al., 2019), our longitudinal data analysis considering individual and time fixed effects and spatial autocorrelation showed a more robust relationship between urban amenities, particularly urban public services and greening rate, and talent distribution between 2000 and 2015. This showed that urban amenities had played an increasingly important role in the decision-making of talent in cities, and thus the distribution of talent had been transforming from an economy-led mode to an economy- and amenity-led mode.

After the 13th Five-Year Plan from 2016, cities in China were encouraged to take into effect various policies to attract talent to settle in. Although few studies have focused on the new trend of talent distribution at the city level during the 13th Five-Year Plan, one conducted at the provincial level has indicated that eastern China had enjoyed a high migration probability of youth talent in 2017, which was consistent with the findings in our research (Li and Xie, 2020). However, western China was also found to attract more educated youth people, while the central part of China had the lowest in-migration probability of youth talent. This might be partly due to the difference in the definition of talent. In addition, Li and Xie (2020) focused on the distribution of the migration rate of talent, while in our study, the stock of talent was used as the measurement. The western part of China may still have a limited scale of talent during the 13th Five-Year Plan, but it has begun to show the tendency of talent concentration.

The spatial concentration pattern of talent at the city level was closely associated with the distribution of economic and amenity factors. As China's economic resources and public service supplies are concentrated in developed metropolitan areas with large populations, the existing pattern of spatial concentration and unbalanced distribution in the pool of talent is expected to persist over time. Further, an increasing scale of the highly educated population has concentrated in eastern coastal China in the fifteen years, while the western and central parts of China have seen severe brain drain. The implementation of several national or regional policies such as the 'China Western Development' and the 'Rise of Central China' seems to be out of operation in alleviating the unevenness in the distribution pattern of talent, which calls for the formulation of more effective talent and regional development policies.

Our results have wide-ranging policy implications. From a national and regional perspective, they emphasize the need for appropriate regional development policies to optimize the pattern of talent. For eastern areas with a high density of talent, policies should be targeted at taking advantage of the positive externalities brought about by the clustering of talent. For the central and western regions, where talent is sparsely distributed, preferential policies should be formulated to give specific financial supports to people, such as young graduates to guarantee their fundamental lives. From a city's perspective, local governments should enhance the economic level of cities by offering more employment opportunities to attract talent (Gu et al., 2020c). Meanwhile, governments should also focus on improving public services and the urban environment, particularly primary education amenities and raising local expenditure on science, technology and education, so that the city can meet the increasing and diverse needs of talent.

6 Conclusions

This paper assesses and seeks to identify key factors shaping the spatial distribution of talent across Chinese cities between 2000 and 2015. Results revealed a high degree of spatial concentration in the distribution of Chinese talent throughout the fifteen-year period in a small number of cities, especially cities in urban agglomerations and provincial capitals in the eastern coastal areas. We present evidence of major spatial inequality in the distribution of talent and while this inequality decreased between 2010 and 2015, it has remained relatively high. Examining the density of talent within each of four economic-geography regions of China also revealed a pattern of rapidly increasing concentration of talent in the eastern region, increasing the gap in the local stock of spatial talent between regions. Only small changes in the local pool of talent were observed in western and north-western cities.

A significant, positive spatial autocorrelation in the spatial distribution of talent across Chinese cities exists. An ESF specification was used to mitigate the effects of spatial autocorrelation and reduce estimation bias. Our modeling results revealed that urban economic opportunities had played a dominant role in shaping the spatial distribution of talent in China. Economic variables were consistently and significantly associated with the local pool of talent. Specifically, regional GDP and average urban employed staff and workers per 10 000 showed strong positive relationships with talent stock. Urban amenities also seem to have played an important role. Model results revealed that the number of middle school teachers per 10 000 students, the ratio of per capita science, technology, and education expenditure, and urban green were persistently positively associated with the stock of talent of the city. Although several other amenity variables did not show relationships with the distribution of talent, our results provided evidence for the effect of public services and greening rate.

Using the data of Chinese highly educated talent at the city level, the present paper measures the average effects of economic- and amenity-related factors on the spatial distribution of talent over 2000–2015. China has gone through significant social changes over this period, which may have influenced the ways in which key contextual economic and non-economic factors contribute to shape the geographic distribution of talent over time. Future studies may estimate the time-variant influence of these factors and how they vary across cities.

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