Chin. Geogra. Sci. 2024 Vol. 34 No. 4 pp. 739−751
https://doi.org/10.1007/s11769-024-1447-4

Springer Science Press
www.springerlink.com/content/1002-0063

Evolution and Determinants of Population Agglomeration in Less Developed Metropolitan Areas: A Case Study of the Taiyuan Metropolitan Area, China

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Abstract: It is of importance to enhance the urban areas' capacity for population aggregation in underdeveloped regions, aiming to rectify the imbalanced and insufficient pattern of economic development in China. Taking the Taiyuan Metropolitan Area (TMA) in central China as a case study, this paper examines the evolutionary process and characteristics of population agglomeration from 2000 to 2020, and identifies factors associated with agglomeration and their spatial effects. The findings indicated that: 1) against the background of sustained population shrinkage in the provincial area, the TMA showed a demographic trend of steady increase, albeit with a decelerated growth rate. In the metropolitan area, urban population size continued to grow rapidly, whereas the rural areas endured sustained losses. Disparities in city size continued to widen, and the polarization of concentrated population in the core cities kept increasing. 2) Agglomerations in both secondary and service industries had significant positive effects on local population agglomeration, with the former effect being stronger. Regional economic development, government fiscal expenditure, and financial advancement all contributed to facilitating local population clustering. From a spatial spillover perspective, service agglomeration and financial development promoted population agglomeration in surrounding areas. Conversely, fiscal expenditure inhibited such agglomeration. As for industrial agglomeration and regional economic development, their spatial spillover effects were non-significant. The results obtained reveal several policy implications aimed at enhancing the population agglomeration capacity of the metropolitan area in underdeveloped regions during the new era.

Keywords: population agglomeration; population shrinkage; spatial spillover effects; Taiyuan Metropolitan Area (TMA), China

Citation: QIN Zhiqin, LIANG Ye, AN Shuwei, DOU Yongjing, 2024. Evolution and Determinants of Population Agglomeration in Less Developed Metropolitan Areas: A Case Study of the Taiyuan Metropolitan Area, China. *Chinese Geographical Science*, 34(4): 739−751. https://doi.org/10.1007/s11769-024-1447-4

1 Introduction

The metropolitan area plays a crucial role in promoting the high-quality development of urbanization in China. Since the 21st century, driven by rapid economic growth and industrialization, there has been a significant migration of people from rural areas to small and medium-sized cities, as well as from these cities to larger ones. Consequently, various metropolitan areas with different scales and levels of development have gradually emerged (Liu and Liu, 2020).

In general, metropolitan areas in underdeveloped re-

Received date: 2023-10-10; accepted date: 2024-02-09

Foundation item: Under the auspices of the Humanities and Social Sciences Fund of the Ministry of Education of China (No. 20YJC790107), Planning Project for Philosophy and Social Sciences of Shanxi Province (No. 2021YJ040), Special Foundation for Science and Development of Shanxi Province (No. 202204031401052)

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gions are less capable of attracting population clusters and driving the development of neighboring cities than those in developed regions (An and Zhang, 2020). This results in disparate regional economic development in China. In response to the unbalanced regional economic development during the new normal stage, China's new urbanization planning has focused on supporting the cultivation of metropolitan areas in underdeveloped regions. Notably, the National Development and Reform Commission (NDRC) issued the 'Guidance on Fostering the Development of Modernized Metropolitan Areas' (NDRC, 2019). This guidance places greater emphasis on the strategic support of metropolitan areas in promoting high-quality economic development in less developed regions. With strong national policy support, these metropolitan areas have indeed demonstrated significant agglomeration effects and driving forces. However, as China enters a phase of moderate economic growth and negative population growth in recent years, competition for population among different regions is intensifying. This poses new challenges to the ability and potential of urban areas in underdeveloped regions to attract populations (Lu, 2019; Liu, 2020; Xian and Chen, 2022). In this context, it is significant to describe the emerging dynamics and tendencies of population agglomeration in urban areas in less developed regions, as well as to decipher the logic of the connection with population aggregation and metropolitan area development.

A metropolitan area is an urban complex that gradually expands outward from a large city as its core (Gaile, 1980; Mao et al., 2014). Population agglomeration is a basic indicator to characterize the development stage, expansion process, and policy effects for metropolitan areas (Davis, 1965; Carbonaro et al., 2018). Research has demonstrated that due to market forces and the agglomeration effect, there exists an inverted U-shaped relationship between urban population concentration scale and economic efficiency (Thisse et al., 1986; Au and Vernon Henderson, 2006). Developmental practices have also revealed that continuous population flow and agglomeration contribute to the 'scale effect' in both developed and underdeveloped regions (Fujita and Thisse, 2003; Melo et al., 2009). However, in developed areas with high levels of urbanization, the massive expansion of urban space has resulted in a number of agglomeration diseconomies such as escalating commuting and housing costs and environmental pollution. This is known as the 'crowding effect' (Xu and Jiao, 2021). Consequently, some economic activities and population overflow from central cities into surrounding areas, thus reorganizing and optimizing the structure and functions of urban. In less developed areas where urbanization levels are low, population agglomeration primarily remains polarized towards central cities while exhibiting weak spillover effects on surrounding regions. In the process of polarization and spillover of population and other factors, the central city and the peripheral area gradually form a highly connected integrated area, i.e., the metropolitan area (Cochrane and Vining, 1988; Li et al., 2010; Chen et al., 2020). The formation and development of metropolitan areas depend on population agglomeration, which is the outcome of industrial agglomeration (Fujita and Thisse, 1996). Driven by market forces, enterprises and various economic elements will choose an optimal location to form agglomeration spontaneously based on the principle of efficiency, thereby spontaneously forming agglomerations. The resulting industrial agglomeration effect helps enhance urban employment and population absorption capacity (Hanson, 2001; Alcácer and Chung, 2014). However, different types of industrial agglomerations have contrasting effects on urban population concentration. Industrial specialization agglomeration with Marshall externality inhibits population concentration, whereas industrial diversification agglomeration with Jacobs externality significantly promotes population concentration (Marshall, 1961; Neffke et al., 2011). Moreover, while influencing local urban population concentration, industrial agglomeration may also have spillover effects on the population concentration in neighboring cities through inter-regional industrial transfers or spatial flow of factors (Wright et al., 1997). The spatial pattern and scale of population concentration in metropolitan areas are also influenced by various factors such as tax structure, public services, and infrastructure among surrounding areas (da Silva et al., 2017; Wang et al., 2022).

The dynamic evolution of population agglomeration is closely correlated with the phase of economic development and changes in urbanization pattern. Metropolitan areas serve as crucial growth poles for regional economic development. Scholars and governments have focused on studying the trends, driving mechanisms, and spatial spillover effects of population agglomeration in metropolitan areas. Existing research focuses on the following aspects: Firstly, it focuses on spatial and temporal changes in population agglomeration density (La Greca et al., 2011; Yu et al., 2022), scale (Fragkias and Seto, 2009), and pattern (Li et al., 2013), and other dimensions to reveal the spatial evolution and functional transformation of metropolitan areas in the process of urbanization. The attention primarily revolves the expansion of multi-center population agglomerations in metropolitan areas (Dökmeci and Berköz, 1994; Meijers and Burger, 2010), decentralization and transformation of central city functions (Duranton and Puga, 2005), as well as integrated development between centers and peripheries (Copus, 2001). Secondly, interdisciplinary methods such as qualitative description, GIS spatial analysis, and econometric model construction are commonly employed for research purposes (McGuirk and Argent, 2011; Grekousis et al., 2013). In recent years, with urbanization processes enhancing spatial interaction and dependence between cities, there has been a growing application of spatial metrology models (Yu et al., 2020; Tong and Qiu, 2020). The spatial Durbin model demonstrates distinct advantages in modeling the implications of urban population expansion and the spatial spillover effects of socioeconomic conditions on urban agglomeration. Thirdly, research has primarily focus on regions nationwide (Chen et al., 2016; Gu et al., 2022), key regions with national strategies (Li et al., 2020; You et al., 2021; Qiang and Hu, 2022), and developed regions in eastern China (Haas and Ban, 2014). However, the formation and development of metropolitan areas exhibit noticeable spatiotemporal heterogeneity. The factors and mechanisms influencing population agglomeration in these areas are complex, diverse, and characterized by distinct dynamics. The implementation of the coordinated regional economic development strategy requires further attention to the evolution of population agglomeration in special types of urban areas, as well as their polarization and spillover effects.

At present, China is undergoing a transitional period characterized by decelerating economic growth and sluggish population expansion. Consequently, the macroscopic pattern of demographic gathering and migration has undergone fundamental transformations (Deng et al., 2022). As a growth-pole of regional economic development, urban areas in underdeveloped regions possess the potential to generate sustained agglomeration effects and substantial driving forces. This has become the key forces to promote high-quality economic development. Therefore, this study focuses on the Taiyuan Metropolitan Area (TMA), China as research case, aiming to analyze the spatiotemporal evolution process, characteristics, and trends of population concentration from 2000 to 2020. Additionally, it employs the spatial Durbin model to identify the factors affecting demographic agglomeration and its spatial spillover effects. The findings are expected to provide valuable research references and decision-making support for promoting high-quality urbanization and fostering coordinated regional economic development in China as well as other developing countries.

2 Materials and Methods

2.1 Study area

The Taiyuan Metropolitan Area (TMA) of China, located in the middle reaches of the Yellow River Basin, is an urbanization area with Taiyuan as the core and consists of four adjacent prefecture-level cities and 18 surrounding counties. Its geographical coordinates are 110°05′E to 114°02′E and 36°50′N to 39°09′N. The Outline of Urbanization Development in Shanxi Province defined the spatial scope of the TMA and divides it into two areas: the core area and peripheral area (Fig. 1). Most existing studies on new urbanization in Shanxi Province have adopted this division, so we follow the scheme in this paper (Lin, 2014).

With abundant coal resources, Shanxi Province accounts for about 25% of the annual raw coal production of China and is a vital base to ensure national energy security. Since the reform and opening-up, the economic progress of Shanxi Province has been relatively sluggish for reasons such as the excessive proportion of resource-based industries and the lack of transportation location advantages (Table 1). While the central city of the TMA is undersized and stunted among the established metropolitan areas in China, the TMA has obvious advantages in terms of population and economic agglomeration. It is the only developed metropolitan area within the provincial territory of Shanxi Province at present. Although the TMA is relatively small in scale and less developed compared to other metropolitan areas in China, it possesses distinct advantages in terms of population agglomeration and economic concentration within the scope of Shanxi Province. Among the

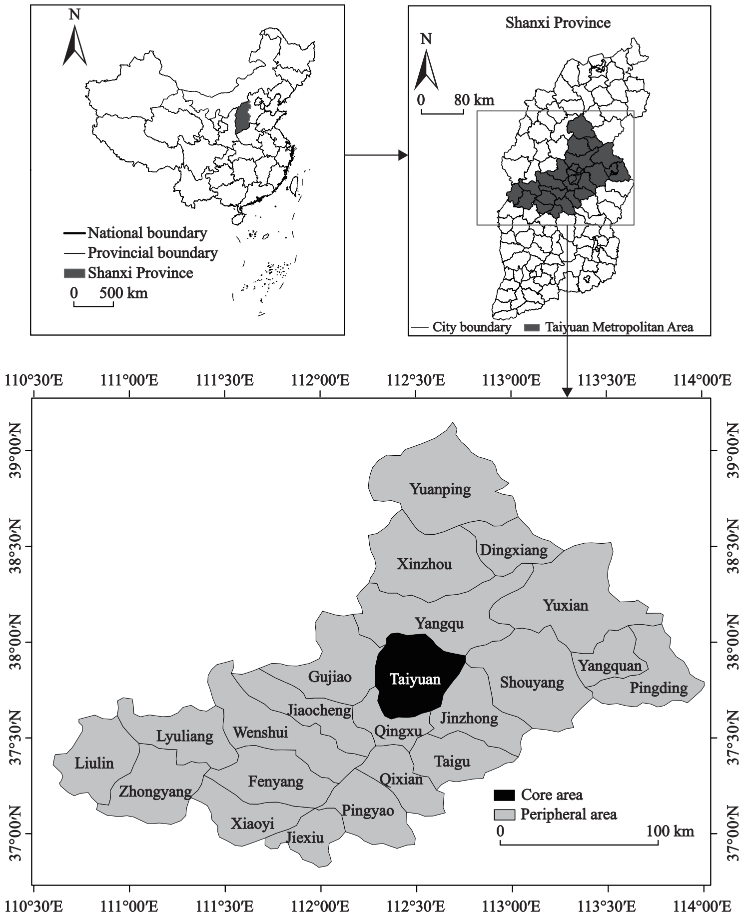

Fig. 1 The location of Taiyuan Metropolitan Area (TMA), Shanxi Province, China. Based on the standard map service website of the Ministry of Natural Resources (http://bzdt.ch.mnr.gov.cn) with the approval number GS(2019)1822, and the boundary of the base map has not been modified

spatial patterns of urbanization in China, the TMA is not only an essential economic growth-pole in Shanxi Province and even in the Yellow River Basin, but also an important fulcrum of ‘Rise of Central China Strategy’. Therefore, it is necessary to explore and fully exploit the population agglomeration potential in the TMA to transform the economic pattern of unbalanced and insufficient development in China.

Table 1 Comparison of main economic and social indicators in 2020

Research scope	GDP per capita / USD	Urbanization rate / %	Per capita disposable income of households / USD
Taiyuan Metropolitan Area	8429.73	73.68	3675.30
Shanxi Province	7325.66	62.53	3655.58
China	10438.72	63.89	4666.80

Notes: the data were calculated according to Shanxi Provincial Statistical Yearbook (SPBS, 2020); USD, US dollar

2.2 Measurements of population agglomeration

(1) Urban Gini coefficient

As a common indicator for measuring the equilibrium of population distribution in cities, the urban Gini coefficient has been widely adopted in urbanization research in recent years (Mucciardi and Benassi, 2023). Here we use the urban Gini coefficient to measure the spatial concentration of the population to describe the unbalance of population agglomeration in the TMA. The coefficient is calculated as follows:

$$G = \frac{1}{2S(N-1)} \sum_{i=1}^{n} \sum_{j=1}^{n} \left| C_i - C_j \right| \tag{1}$$

where G is the urban Gini coefficient; N denotes the number of cities in the TMA; S is the total population size of the TMA; and C_i and C_j are the population size of urban areas i and j, respectively. The index value is within the range [0, 1]. The higher the value of G, the more concentrated is the population distribution and the stronger is the imbalance in population agglomeration.

(2) Urban primacy index

Urban primacy is the ratio of the population of the largest city to that of the second largest city in the urban system of a region or country. It indicates the influence and driving effect of the largest city on other cities. Taiyuan is the primary and core city in the TMA. We use the urban primacy index (Chun and Kim, 2022) as a measure of the relative population concentration of Taiyuan, and to characterize its radiating and driving effect on other cities in the TMA.

2.3 Spatial econometric models

The scale of population agglomeration in a city is not only related to the city's own development capacity but also has spatial spillover effects on neighboring cities through industrial agglomeration and transfer, labor mobility, and infrastructure integration, among other things. Spatial autocorrelation is common in most spatial data, and spatial econometric models can address spatial dependence problems that cannot be solved by ordinary linear regression (Anselin and Griffith, 1988).

2.3.1 Spatial autocorrelation analysis

Spatial autocorrelation refers to the correlation between variables values observed due to the spatial proximity of observation points. We used the Moran's I to examine the spatial autocorrelation of population agglomeration in the TMA and to explore the spatial correlation and differences in population agglomeration in the overall pattern (Kelejian and Prucha, 2001). The index is calculated as:

$$\text{Moran's } I = \frac{\sum_{i=1}^{n}\sum_{j=1}^{n} w_{ij}(X_i - \bar{X})(X_j - \bar{X})}{1/n \sum_{i=1}^{n}(X_i - \bar{X}) \sum_{i=1}^{n}\sum_{j=1}^{n} w_{ij}} \tag{2}$$

where X_i and X_j are the population size in cities i and j, respectively; $\bar{X}$ is the average of all observations; n denotes the total number of cities; and w_{ij} is a spatial contiguity weight matrix. Moran's I generally falls in the range [−1, 1]. The closer Moran's I is to 1, the higher is the degree of similarity in population size between cities; the closer Moran's I is to −1, the higher is the degree of difference in population size between cities.

2.3.2 Spatial econometric models

Common spatial econometric models include the spatial Durbin model (SDM), spatial error model (SEM), and spatial lag model (SLM). The SEM is used to study the influence of the spatial error term for a neighborhood on local explanatory variables, while the SLM focuses on interaction between explained variables in each region. The SDM considers the influence of the spatial error term and the spatial lag term on explained variables together. Under certain conditions, the SDM can be converted into an SEM and SLM (Mur and Angulo, 2009). On the basis of previous results, the SDM takes the following form:

$$Y = \delta WY + \beta X + \theta WX + \alpha + \mu + \lambda + \varepsilon \tag{3}$$

where Y is the dependent variable (population size of cities); X is the explanatory variable; W is a spatial weight matrix, in which the Queen-type first-order contiguity matrix can be adopted; δ is the spatial lag effect of the explained variables; β is the influence of explanatory variables on the explained variables; α *is* the optional individual effect; μ is the optional time effect; α is a constant term; θ is the spatial lag coefficient for the explanatory variable; and ε is a random disturbance term, with $\varepsilon \sim N(0, \sigma^2)$.

The SEM takes the following form:

$$Y = \beta X + \alpha + \mu + \lambda + \rho W\varphi + \varepsilon \tag{4}$$

where ρ is the effect intensity of random error; φ is a spatial error term.

The SLM takes the following form:

$$Y = \delta WY + \beta X + \alpha + \mu + \lambda + \varepsilon \tag{5}$$

Following previous research, we use the Lagrange multiplier (LM) and the likelihood ratio (LR) to compare the performance of different models to determine the specific form of a suitable spatial econometric model. Results for the LM and its robustness tests show that the LM (lag), LM (error), Robust LM (lag), and Robust LM (error) all rejected the null hypothesis at a significance level of 1%. This indicates that all the variables and error terms of the model are spatially correlated. Therefore, it is more suitable to choose an SDM that considers both a spatial lag term and a spatial error term. Furthermore, according to results for the LR test, all the statistics passed the significance test at the 1% level, and the LR test results were consistent with the LM test. Moreover, the Hausman test statistic was 106.69 (P < 0.01), so we selected the SDM based on a fixed effect.

To solve the endogeneity problem for the model, maximum likelihood estimation was used to estimate the regression.

2.3.3 Variable selection

Economic agglomeration theory shows that agglomeration externalities can generate incremental returns via spillover effects and the interactions between enterprises. Elements of production, such as labor and human capital, are concentrated in cities for higher returns, and the scale of the urban population expands accordingly. The agglomeration effect generated by population expansion promotes the improvement of labor productivity, which further leads to the larger-scale migration and agglomeration of the population. Thus, industrial agglomeration is the key basis for population agglomeration. Moreover, owing to differences in industrial characteristics, the ability of secondary industry and services to create employment opportunities will change significantly at different stages of industrialization. Here, we take the level of industrial and service agglomeration as the core explanatory variables, measured using the location quotient (Billings and Johnson, 2012). The values are calculated as follows:

$$S_i = \frac{E_{im}/E_m}{E_i/E} \quad S_i' = \frac{E'_{im}/E'_m}{E_i/E} \tag{6}$$

where E_{im} and E_m are the gross industrial output value of city i and the TMA, respectively; E'_{im} and E'_m are the gross service industry output value of city i and the TMA, respectively; E_i is the GDP of city i; and E is the GDP of the TMA. The higher the values of S_i and S'_i, the higher the respective degrees of industrial and service agglomerations in city i.

To minimize the estimation bias caused by omitted variables, we selected economic development level (*Lnpgdp*), fiscal expenditure (*Exp*), and financial support (*Fin*) as control variables with reference to existing research findings (Gan et al., 2021). By providing cities with more employment opportunities, better welfare for residents, and more convenient and comprehensive infrastructure, these drivers attract large-scale population clustering to urban areas.

2.3.4 Robustness tests

According to the First Law of Geography, the intensity of spatial interaction between spatial units is reflected by their distance (Miller, 2004). To ensure the robustness of our findings, this study employs a geographical distance spatial weight matrix for maximum likelihood estimation of the spatial Durbin model. The specific formulation for the geographical distance spatial weight matrix is as follows:

$$W_{ij} = \begin{Bmatrix} (\frac{1}{d_{ij}})^2, \ if\ i \neq j \\ 0, \ if\ i = j \end{Bmatrix} \tag{7}$$

where d_{ij} is the spherical distance between spatial units i and j in the TMA calculated in terms of latitude and longitude data.

2.4 Data sources

The permanent resident population and registered population are two commonly utilized statistical indicators in population research within China. However, due to the phenomenon of ‘separation of people and households’ in China, there exists a deviation between the urban registered population data and the actual resident population data (Chan, 2003). In contrast, permanent residents encompass the floating population within their statistical scope, providing data that is more closely aligned with the real population situation (Li et al., 2020). Furthermore, the resident population serves as not only a universal indicator for global demographic statistics and data release but also as a primary basis for economic and social development planning at all levels of Chinese government. Therefore, this study employs the resident population as a fundamental index to measure population agglomeration within the TMA.

The resident population data primarily originate from two sources: China’s census data and statistical yearbooks (Li et al., 2020).

Based upon the comparison, we observe minimal disparities between the census data of Shanxi Province since 2000 and the corresponding data in the statistical yearbook. However, Chinese census data are collected every ten yr, whereas statistical yearbooks provide population data for consecutive years. To fulfill the requirements of the econometric model in this study, the population data utilized mainly derive from various statistical yearbooks such as China City Statistical Yearbook (NBS, 2020a), China County Economic Statistical Yearbook (NBS, 2020b), Shanxi Provincial Statistical Yearbook (SPBS, 2020), and statistical bulletins issued by certain cities and counties. For missing data for specific cities in certain years, an interpolation method based on recent-year information is employed for estimation purposes. Based on these considerations, panel data for TMA spanning from 2000 to 2020 are constructed.

The administrative division map utilized in this study is based on 1∶250 000 fundamental geographic data sourced from the Data Center for Resources and Environmental Sciences at the Chinese Academy of Sciences (RESDC, 2024).

3 Results and Analyses

3.1 Spatial and temporal changes in population agglomeration in the TMA

Compared with the population shrinkage trend in Shanxi Province, the TMA exhibits a continuous increase in population agglomeration, albeit at a decelerated rate. According to statistics, from 2000 to 2020, the total population of the Taiyuan Metropolitan Area increased from 9 884 100 to 12 660 600, an overall growth of 2 776 500. Specifically, the total population growth rate was 14.99% from 2000 to 2010, and decreased slightly to 11.40% from 2010 to 2020. In the same period, the total population of Shanxi Province witnessed an increase of 2.427 million individuals. Specifically, there was a growth rate of 10.05% from 2000 to 2010; however, it is projected to decline by 2.34% from 2010 to 2020. This indicates that since the year 2000, following a phase of rapid population expansion, Shanxi Province has entered into a phase characterized by population contraction. Against this backdrop, although the pace of population concentration in the TMA has gradually decelerated after experiencing rapid growth initially, the magnitude of such concentration continues to exhibit an upward trajectory. This phenomenon reflects the enduring tendency for continuous centripetal agglomeration of demographic elements during the developmental stage of a metropolitan area.

The urban population in the TMA continues to experience rapid growth, while the rural population is undergoing significant decline. From 2000 to 2020, the urbanization rate of the TMA increased from 38.96% to 73.68%. During the period from 2000 to 2010, there was a rise of 9.09% in urbanization rate, followed by an increase of 25.18% from 2010 to 2020. These figures indicate that there has been a sustained high growth rate in terms of urban population concentration within the TMA over recent years. During this same period, the rural population experienced decreases of 27.14% and 24.19% respectively. This suggests that the TMA is currently undergoing a phase of rapid expansion with continuous convergence of population elements towards urban areas, consequently leading to an expanding gap between urban and rural populations as well as further exacerbating imbalances in their distribution patterns. It can be predicted that in upcoming years, there will continue to be an influx of people into cities within the TMA and thus intensifying trends related to rural 'hollowing out' caused by outmigration.

The gap in urban population size continues to widen, and the population concentration in the core area continues to polarize. The Gini coefficient was utilized to characterize the changing trend of population agglomeration in the Taiyuan Metropolitan Area. The findings revealed (Table 2) that from 2000 to 2020, there was a consistent increase in the Gini coefficient of the TMA, indicating a tendency towards centralized distribution of population elements within this region. Moreover, it signifies an ongoing improvement in the degree of population agglomeration and a gradual widening of the scale gap between cities during this study period. The primacy of Taiyuan City as the core within the TMA is employed to depict changes in population agglomeration. The results demonstrate that from 2000 to 2020, there has been a continuous annual increase in the primacy index for the TMA as well. This indicates that polarization effects on population towards the core area of the TMA continue to strengthen, further confirming our research judgment that this metropolitan area is currently experiencing a growth stage.

Cities closer to the core city primarily exhibit a growth-oriented development pattern, whereas cities farther away tend to adopt a shrinkage-oriented approach (Fig. 2). For instance, Jinzhong City experienced the largest increase in population growth rate,

Table 2 Changes in population agglomeration in Taiyuan Metropolitan Area (TMA) in 2000, 2005, 2010, 2015 and 2020

Year	Urban Gini coefficient	Urban primacy index
2000	0.1956	0.2588
2005	0.1947	0.2574
2010	0.2173	0.3017
2015	0.2221	0.3075
2020	0.2497	0.3589

rising from 19% to 42%. In recent years, Shanxi Province has implemented the 'Big Taiyuan' strategy, with administrative efforts playing a crucial role in resource allocation and population distribution guidance. As Taiyuan's urbanization progresses steadily, the construction and industrial layout of large-scale industrial parks and university towns have expanded towards the south, significantly enhancing Yuci's capacity for population absorption. Similarly, during the process of promoting the integration of Taiyuan and Xinzhou, Yangqu and Xinzhou, and other northern cities of Taiyuan have witnessed rapid population concentration. Lyuliang City in western Shanxi demonstrates substantial population growth rates indicative of its strong ability to attract populations from hinterland cities. Most small cities located far from Taiyuan are situated within either the Taihang or Lyuliang Mountain areas, where natural environmental carrying capacity is limited and traditional agriculture remains prominent. Consequently, population flows tend to gravitate towards medium-sized and larger cities offering better public service facilities as well as greater employment opportunities; meanwhile smaller cities with weaker abilities to attract populations receive fewer inflows.

3.2 Influencing factors and spatial spillover effects

3.2.1 Spatial autocorrelation characteristics of population agglomeration

Based on Moran's I index, the spatial correlation and agglomeration characteristics of population distribution in the TMA were further analyzed. The results indicate

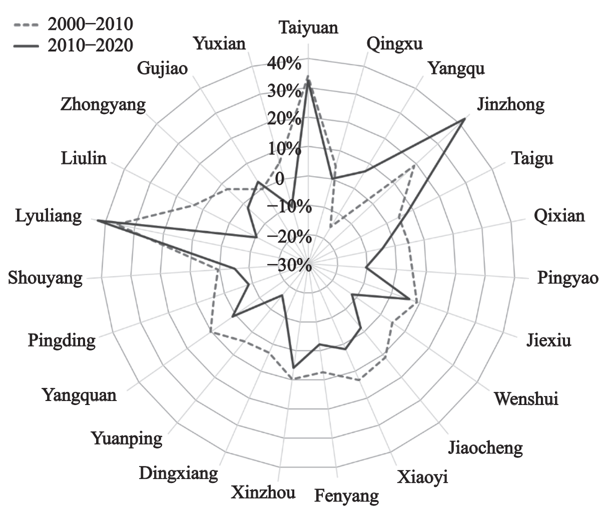

Fig. 2 Total population growth rate in the Taiyuan Metropolitan Area (TMA) , China during 2000–2010 and 2010–2020

that from 2000 to 2020, the Moran's index of population size in the TMA exhibited a change range of [−0.35, −0.24]. All statistical results passed a normality test with Z-values showing increasing significance at a 5% level. This suggests a significant spatial negative correlation in recent years for the population size of the TMA.

3.2.2 Analysis of baseline regression results

The spatial panel data of the TMA from 2000 to 2020 was utilized for fitting analysis using regression models, including ordinary least squares (OLS), spatial lag model (SLM), spatial error model (SEM), and the spatial Durbin model (SDM). Results indicated that the SDM with fixed effects exhibited a higher degree of fit (Table 3). Consequently, this study employs the SDM to examine the influencing factors and spatial spillover effects of population agglomeration in the TMA.

The regression coefficient for S_i was found to be 0.1568, demonstrating statistical significance at the 1% level. This indicates that industrial agglomeration plays a crucial role in absorbing population agglomeration during the development and growth stages of the TMA. The regression coefficient for S'_i is 0.1372, which also exhibits significant positive correlation with population agglomeration in the TMA based on a significance test at the 10% level. However, it is worth noting that while service industry agglomeration does contribute to population concentration, its impact is relatively weaker compared to industrial agglomeration. This can be attributed to most cities in the Taiyuan Metropolitan Area being resource-based cities with a high proportion of coal resources industries. Despite recent progress in transforming towards a more diversified economy, industrial agglomeration continues to play a pivotal role in driving spatial evolution within this metropolitan region.

Control variables such as *Lnpgdp*, *Exp*, and *Fin* are positively correlated with population agglomeration and statistically significant. These results show that urban population agglomeration within the TMA is a staged feature of regional economic development, which is conducive to creating more jobs and attracting migration of a labor force from rural areas and smaller cities to urban centers.

3.2.3 Decomposition of the spatial effect

The partial differential method was employed to further decompose the overall impact of SDM into its direct and indirect effects (LeSage and Pace, 2009). The direct ef-

Table 3 Regression results for ordinary least squares (OLS) and the spatial econometric models

Variable	OLS		SLM		SEM		SDM	
	Coef.	*T* score	Coef.	*T* score	Coef.	*T* score	Coef.	*T* score
S_i	0.6253**	2.2735	0.0950**	2.0599	0.0955**	2.0832	0.1568***	3.4225
S'_i	2.0475***	5.2469	0.0648	0.7712	0.0796	0.9629	0.1372*	1.6918
Lnpgdp	0.5623***	5.9022	0.1653***	4.6471	0.1751***	4.9618	0.1263***	3.6486
Exp	−0.0261	−0.6347	0.0192*	1.7973	0.0178*	1.6625	0.0195*	1.8805
Fin	0.0001	1.5769	0.0003***	3.9262	0.0003***	3.7101	0.0002**	2.2612
$W \times S_i$	–	–	–	–	–	–	−0.0429	−1.0102
$W \times S'_i$	–	–	–	–	–	–	0.1903*	1.7745
W×*Lnpgdp*	–	–	–	–	–	–	0.0167	0.2768
W×*Exp*	–	–	–	–	–	–	−0.0336**	−2.2142
W×*Fin*	–	–	–	–	–	–	0.0003*	1.8693
Constant	2.4665**	2.4237	–	–	–	–	–	–
R^2	0.8312		0.7540		0.7622		0.5647	
Log likelihood	–		309.5299		310.6417		346.0375	

Notes: *, **, and *** indicate significance at the 0.1, 0.05, and 0.01 levels, respectively. *Lnpgdp*, economic development level; *Exp*, fiscal expenditure; *Fin*, financial support. $W \times S_i$, $W \times S'_i$, *W*×*Lnpgdp*, *W*×*Exp* and *W*×*Fin* represents the spatial spillover effect of influencing factors. SLM, spatial lag model; SEM, spatial error model; SDM, spatial Durbin model.

fect refers to the influence of the explanatory variable on the local explained variable, while the indirect effect represents the spatial spillover effect of the explanatory variable on neighboring explained variables (Table 4).

The coefficient of the direct effect of S_i is 0.1585, and based on a significance test at the 1% level, it demonstrates that the industrial agglomeration in the TMA has a highly significant promoting impact on population concentration within the city. The coefficient of the indirect effect of S_i is –0.0548, indicating a negative spatial spillover effect of industrial agglomeration on population concentration in surrounding cities. This may be attributed to factors such as labor, technology, and capital being drawn from these surrounding cities during the process of central city's industrial agglomeration, thereby inhibiting population concentration growth in those areas.

The direct and indirect effect coefficients of S'_i are 0.1321 and 0.1690 respectively, both significant at the 10% level. This suggests that service industry agglomeration contributes to the population agglomeration of both the local and surrounding cities. In comparison to industrial agglomeration, service agglomeration exhibits a more pronounced spillover effect on population concentration due to its ability to effectively reduce transaction costs, enhance urban efficiency through knowledge spillover effects, and augment the capacity for population concentration in both the local and sur-

Table 4 Spatial Durbin model (SDM) decomposition results for the total spatial effect based on the contiguity weight matrix

Variable	Direct effect		Indirect effect		Total effect	
	Coef.	*T* score	Coef.	*T* score	Coef.	*T* score
S_i	0.1585***	3.4712	–0.0548	–1.3229	0.1036*	1.7211
S'_i	0.1321*	1.7085	0.1690*	1.7326	0.3011***	2.8574
Lnpgdp	0.1248***	3.6147	0.0071	0.1215	0.1319**	2.2143
Exp	0.0209**	2.0097	–0.0334**	–2.3304	–0.0125	–0.6922
Fin	0.0002**	2.3421	0.0003**	2.0681	0.0005	0.4667

Notes: *, **, and *** indicate significance at the 0.1, 0.05, and 0.01 levels, respectively. The meanings of variable are same as Table 3 rounding cities.

The coefficient of the direct effect of *Lnpgdp* is positively and significant at the 1% level, while the indirect effect is not statistically significant. This suggests that it promotes population agglomeration within the city but has a weak influence on population agglomeration in surrounding cities.

The coefficients for both the direct and indirect effects of *Exp* are 0.0209 and –0.0334, respectively, and both are statistically significant at the 5% level. This indicates that government financial expenditure capacity stimulates population agglomeration within the city but restricts it in surrounding cities. The coefficients for the direct and indirect effects of *Fin* are significantly positive, but both are less than 0.001, which means that although financial development is conducive to improving urban population agglomeration in the local and surrounding areas, its effect is not noticeable. It can be observed that financial industry development in the TMA does not provide sufficient support for urban population agglomeration.

3.2.4 Robustness test results

Table 5 and Table 6 present the results for SDM regression and effect decomposition of the spatial weight matrix for geographic distance, from which the signs of coefficients for each variable remained unchanged and the significance variations for variables were slight. This confirmed the robustness of the above estimation results.

4 Conclusions and Suggestions

4.1 Conclusions

Taking the TMA in Shanxi Province as an illustrative case, this study examines the evolutionary process, influencing factors, and spatial spillover effects of population agglomeration in less developed metropolitan areas of China from 2000 to 2020. The key findings are as follows:

(1) Against the backdrop of continuous provincial population shrinkage, population agglomeration in metropolitan areas has shown a consistent upward trend, albeit with a decelerating pace. Within the metropolitan area, urban populations continue to grow rapidly while rural populations experience significant decline, resulting in a convergence towards urban centers and posing

Table 5 Results for the spatial Durbin model (SDM)

Variable	Direct effect		Variable	Spatial spillover effect	
	Coef.	*T* score		Coef.	*T* score
S_i	0.1520^{***}	3.3721	$W\times S_i$	−0.0764	−0.5325
S'_i	0.0542^{*}	1.6642	$W\times S'_i$	0.3389^{**}	2.1434
Lnpgdp	0.1190^{***}	3.3658	$W\times$*Lnpgdp*	0.3000^{***}	3.3366
Exp	0.0322^{***}	2.8013	$W\times$*Exp*	-0.0134^{***}	−4.4212
Fin	0.0003^{***}	3.0992	$W\times$*Fin*	0.0002	0.5457
R^2	0.7746		Log likelihood	337.2254	

Notes: *, **, and *** indicate significance at the 0.1, 0.05, and 0.01 levels, respectively. The meanings of variable are same as Table 3

Table 6 Decomposition results for the spatial Durbin model (SDM) based on the geographic distance matrix

Variable	Direct effect		Indirect effect		Total effect	
	Coef.	*T* score	Coef.	*T* score	Coef.	*T* score
S_i	0.1507^{***}	3.3326	0.0185	0.3324	0.1692^{**}	2.5113
S'_i	0.0358^{*}	1.8409	0.2573^{*}	1.9371	0.2931^{**}	2.4326
Lnpgdp	0.1027^{***}	2.8733	0.2119^{***}	3.1642	0.3147^{***}	5.0199
Exp	0.0341^{***}	3.1612	-0.0195^{**}	−1.9928	0.0145	0.7194
Fin	0.0001^{***}	3.0687	0.0004^{*}	1.6613	0.000^{5***}	2.9730

Notes: *, **, and *** indicate significance at the 0.1, 0.05, and 0.01 levels, respectively. The meanings of variable are same as Table 3 risks of rural 'hollowing out'. Furthermore, there is an expanding gap in city sizes among cities within the metropolitan area, intensifying the polarization effect of population gravitating towards core cities. In outer cities of the metropolitan area, those closer to the core city witness population growth dominance while those farther away face population reduction. Overall, under this new development pattern, less developed areas still exhibit a distinct trend of 'single core agglomeration' characterized by dual reinforcement from provincial and urban population agglomerations towards central cities.

(2) The proportion of traditional industries in underdeveloped regions is relatively high, while the service industry lags behind in terms of development. Both industrial and service agglomerations have significant positive effects on population concentration in less developed metropolitan areas, but industrial agglomeration has a greater impact than that of the service industry. Regional economic development, government fiscal expenditure, and financial level all have positive effects on population concentration, although the influence of financial level remains weak. Further analysis reveals that industrial agglomeration significantly promotes population concentration within cities but not surrounding ones; whereas service industry agglomeration benefits both urban and surrounding populations. While regional economic development and financial environment promote city population concentration, their spillover effect on surrounding cities is not obvious. Municipal government's fiscal expenditure capacity does not benefit the population concentration of surrounding cities.

4.2 Suggestions

Agglomeration signifies efficiency, and the spatial evolution of population agglomeration in a market economy serves as a spatial manifestation of economic efficiency. It is noteworthy that many provincial capitals serve as core cities within these underdeveloped metropolitan areas. For the coming years, given the population decline trend within provinces in underdeveloped regions, there is a need for vigilance regarding the potential risks of population shrinkage for the high-quality development of metropolitan economies. This issue bears relevance to effectively implementing major strategies aimed at narrowing regional disparities and achieving coordinated regional development at a national level under the new development pattern. In summary, the findings of this paper have clear policy implications:

(1) Upgrading the level of industrialization and optimizing the mode of agglomeration. Underdeveloped areas exhibit a lower degree of industrialization, resulting in a lack of industrial support for metropolitan development. It is imperative to upgrade the level of industrial modernization and expedite the transition towards low-carbon industry driven by innovation. By spillover effects from modern service industries and innovative activities, the industries of inter-city and urban-rural areas will be further integrated, thus stimulating the potential for population clustering and employment absorption in the metropolitan areas of less developed regions.

(2) Improving the provision of public services. The government should enhance the allocation of public resources in metropolitan areas through measures such as taxation and financial transfer payments. Specifically, priority should be given to bolstering support for key public services like education and healthcare, leveraging their spillover effects to expand the reach of these services from central cities into surrounding regions. This will facilitate the comprehensive integration and coordinated development of basic public services between central cities and peripheral areas.

(3) Weakening the predominant role of administrative power. In recent years, the new urbanization has reinforced by 'strengthening the development of metropolitan areas led by central cities'. However, this policy' s siphoning effect may exacerbate the disparity between central cities and peripheral cities. In the future, competition for population among China's metropolitan areas will intensify further. To enhance population concentration in less developed regions, they should follow the law of urbanization development. On the one hand, to steadily boost the population-carrying capacity in the evolution of the polarization and spillover of metropolitan areas. On the other hand, a regional value should be structured to proactively integrate the economic development pattern of nationwide coordination.

Despite the innovative and significant findings from this study, there are still limitations that can guide future research. Firstly, considering the existing research and data availability, this study is confined to the spatial scale of urban and county areas. However, studying at a more micro scale could reveal different scenarios, which should be the focus of future research. Secondly, the evolution mechanism of population agglomeration in metropolitan areas tends to be comprehensive and complex in the later period of urbanization, which can strengthen the discussion on the intermediary mechanism such as institutional culture, technological innovation, carbon emission, and opening to the outside world. It is worth noting that other potential mechanisms may also exist.

Conflict of Interest

The authors have no relevant financial or non-financial interests to disclose.

Author Contributions

All authors contributed to the study conception and design. The first draft of the manuscript was written by QIN Zhiqin. Material preparation, data collection and analysis were performed by QIN Zhiqin, LIANG Ye, AN Shuwei and DOU Yongjing. All authors read and approved the final manuscript.

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