Impact of Population Density on Spatial Differences in the Economic Growth of Urban Agglomerations: The Case of Guanzhong Plain Urban Agglomeration, China

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Abstract: In the new period of ups and downs in the international environment, it is necessary to seek a new endogenous impetus for the economic growth of urban agglomerations. Population agglomeration provides a new idea to explain the spatial differences in the economic growth of urban agglomerations. Thus, we ask the question, does population agglomeration affect the spatial differences in the economic growth of urban agglomerations, and how? This study first measured the spatial differences in district- and county-scale economic growth in China’s Guanzhong Plain urban agglomeration from 2005 to 2020 and then constructed an empirical formula to calculate the impact of population density on the urban agglomeration’s economic growth, taking into account the roles of both intra- and inter-district and county interactions. Thus, based on the population density data extracted from nighttime lighting data, we analyzed the impact of population density on economic growth within urban agglomerations, as well as the extent of the impact of population density on economic growth when incorporating spillover effects from neighboring districts and counties. The results indicate that, firstly, the Guanzhong Plain urban agglomeration in China has formed a “core-periphery” development pattern, with the main urban areas of Xi’an–Xianyang and Baoji as the core and the core area gradually spreading out to the neighboring districts and counties of their cities. Secondly, population density can significantly and steadily promote the economic growth of the districts and counties within the urban agglomeration, and the population agglomeration of districts and counties with railway stations can have a stronger effect on the economic growth of these districts and counties. Third, the agglomeration of economic and demographic factors in neighboring counties has a positive spillover effect on the local economy, while the positive impact of population density on economic growth remains unchanged when it is integrated into the spillover effect of neighboring counties. This study not only provides a theoretical basis for systematically exploring the influence of population density on the economic growth of urban agglomerations but also provides a reference for local governments to formulate policies related to regional economic development and spatial territorial planning. According to the research conclusion, this study suggests that local governments can continue to promote the regional development policy of spatial agglomeration and intensive land planning, strengthen the construction of the industrial chain and road network within the urban agglomeration, and deepen the network connection between districts and counties.

Keywords: economic growth; population density; spatial difference; district and county scale; urban agglomeration
1. Introduction

As a spatial form emerging from the middle and advanced stages of urbanization, urban agglomerations are not only an important carrier of regional economic development [1], but also a key gateway for the world to enter China and for China to enter the world [2]. The spatial differences in the economic growth of urban agglomerations has always been a major concern in economic geography, and academics have carried out a large number of empirical studies down to the district and county scales. Although a clear “core-periphery” spatial pattern within the urban agglomerations has been identified [3,4], the evolution trend of this spatial pattern is still unclear, especially for the inland urban agglomerations in China, which still need a lot of basic research. Moreover, a large number of studies on the explanation mechanism of the spatial differences in the economic growth of urban agglomerations have identified the important contribution of exogenous factors such as capital stock, technological progress, foreign trade dependence, institutional change, etc. [5,6]. However, the global financial crisis, COVID-19, and other pandemics have gradually worsened the international trade environment, and the arrival of the Lewis turning point has caused the disappearance of demographic dividends in Chinese cities [7]. The traditional urbanization model that relies on cheap labor and cheap land can no longer meet the new needs of high-quality economic growth of Chinese urban agglomerations in the new period [8]; therefore, it is necessary to seek an “endogenous new driving force” for the economic growth of urban agglomerations [9,10]. An “Agglomeration economy”, which is a high concentration of population, capital, and other factors in a specific space, produces the interaction process of spatial spillover effects such as sharing, matching, and learning [11], which provides a new way of thinking for the study of the mechanisms of the spatial differences in economic growth of urban agglomerations in China [12]. In modern society, with the rapid development of technology and information, indicators measuring the overall degree of agglomeration of a city, such as population agglomeration, have become the focus of the research on the agglomeration economy of cities. Endogenous population density has been recognized to play an important role in the economic growth of urban agglomerations [13,14]; however, fundamental and systematic research on whether and how population density contributes to the economic growth of urban agglomerations is still lacking.

The Guanzhong Plain urban agglomeration, as the frontier of China’s “The Belt and Road” westward development, is facing the opportunities and challenges brought about by the new macroeconomic trend. On the one hand, a large amount of capital and labor is gradually gathering in the Guanzhong Plain urban agglomeration. Influenced by the general decline in purchasing power and the general increase in labor cost in other countries, a large number of manufacturing enterprises on the eastern coast of China have moved to the central and western regions. While the floating population continues to gather in the eastern mega-cities, it has also begun to massively cluster in the important western urban agglomerations [15]. On the other hand, the development of the Guanzhong Plain urban agglomeration is still in the initial stage, with an economic scale only one-fourth that of the Yangtze River Delta, and a population density that is in the middle-to-low range among the 19 urban agglomerations in the country [16]. In terms of empirical research, most of the existing studies have analyzed the more mature eastern and central urban agglomerations such as the Pearl River Delta [17], the Yangtze River Delta [4], Beijing–Tianjin–Hebei, and Chang–Zhu–Tan, etc., but there is still a lack of basic research on the spatial differences in the economic growth of the urban agglomerations in the Guanzhong Plain, especially the endogenous growth mechanism of the spatial differences.

This study takes the case of the Guanzhong Plain urban agglomeration in China, which still needs a lot of basic research, and based on the analysis of the spatial differences in district- and county-scale economic growth in China’s Guanzhong Plain urban agglomeration from 2005 to 2020, we then constructed an empirical formula for determining the impact of population density on the urban agglomeration’s economic growth that takes into account the roles both intra- and inter-city interactions. We investigated the impact
of population density while incorporating the spillover effects of neighboring districts and counties on the economic growth of the Guanzhong Plain urban agglomeration in China. This work not only provides a theoretical basis for systematically exploring the impact of population density on the economic growth of cities/urban agglomerations, but also provides a reference for local governments to formulate policies related to regional economic development and spatial territory planning.

Section 2 presents a literature review on the topic of spatial differences in economic growth in urban agglomerations as a result of population agglomeration. Section 3 presents a formal framework for our empirical work and describes the data. Section 4 presents our results on the relationship between spatial differences in economic growth in urban agglomerations and population agglomeration. Section 5 presents conclusion and discussion.

2. Literature Review

In view of the spatial differences in the economic growth of urban agglomerations in China, academics have generally found that there is an obvious “core-periphery” spatial pattern within urban agglomerations. The central place theory, which discusses the spatial structure of German regions in the early stage, holds that the optimal urban system is a group composed of a series of non-central cities around a central city, and each city is interdependent and develops together. Krugman vividly describes the characteristics of the equilibrium space of the American metropolitan area by constructing a “center-periphery” endogenous development model [18]. Empirically, metropolitan areas in most countries in the world have experienced or are experiencing a continuous transfer of population, capital, and other factors from the periphery to the core areas [19]. An empirical study on the spatial pattern of urban agglomerations in China also found an obvious “core-periphery” spatial pattern. Hu studied the 1990–2007 district- and county-scale data and pointed out that the absolute core of the Yangtze River Delta is still Shanghai, and that its multilevel driven situation is not yet obvious [4]. In the early 2010s, the Guanzhong Plain urban agglomeration in western China still had Xi’an as its absolute core [13,20]. In view of the spatial evolution characteristics of the economic growth of urban agglomeration, the existing research conclusions have not reached a consensus. On the one hand, some studies suggest that the economic gap within urban agglomerations is narrowing. Brezzi found that the reduction in transport and communication costs has prompted the transformation of OECD countries from monocentric urban developments to integrated urban center and sub-center developments [21]. Compared with European countries that began to develop inter-city network systems, the United States is still dominated by large urban development, and the high cost of living has prompted the transformation of regional spaces to inter-city co-developments [22]. Huang pointed out that the Pearl River Delta’s level of economic convergence was higher, and its manufacturing development had shifted from a one-way agglomeration stage to a stage where agglomeration and diffusion coexisted [17]. Moreover, the second- and third-order population sizes of cities within the urban agglomerations in western China also showed a rapid growth trend [23]. On the other hand, some studies show that the economic spatial differences between China’s cross-provincial urban agglomerations are still increasing year by year. Peng found that the economic differences in the Chengdu–Chongqing urban agglomeration showed a fluctuating upward trend between 1995 and 2008 [24]. Yu pointed out that in the early 2010s, the Hubao–Eyu urban agglomeration was in an evolutionary pattern in which there was increasing polarization of the strong and marginalization of the weak cities [25]. Zeng used the more objective NPP/VIIRS nighttime lighting data to find that the economic level of counties in the provincial border area of Xiang-E-Gan showed obvious “pyramid” characteristics, and the top of the “pyramid” was becoming narrower [26].

Although traditional exogenous influencing factors of the spatial differences in the economic growth of urban agglomerations, such as capital stock, technological progress, and foreign trade dependence, still play an important role, they cannot perfectly explain the long-term development of regional economies [27]. In particular, for modern cities
“endogenous development” has become an important engine for economic growth [9,10]. The agglomeration economy, as a classic theory that is intrinsically linked to urban economic growth, not only successfully incorporates spatial elements into the regional economic growth model [28], but also clearly describes the emergence and development of the intra-city space and the urban hierarchical system [29]. It provides a new way to study the explanatory mechanism of spatial differences in the economic growth of urban agglomerations [12]. Location entropy, the Thiel index, and other indicators that measure the degree of single-industry agglomeration [30], as well as specialization, diversity, and other indicators reflecting the degree of agglomeration of core industries in the city [31], are the traditional criteria for measuring the agglomeration economy. However, in modern urban agglomerations where science, communication, and other technologies are developing at a rapid rate, the roles of service clusters and knowledge spillovers in urban agglomerations are becoming more and more prominent [22]. Indicators measuring the overall degree of urban agglomeration, such as population agglomeration, have begun to become the focus of attention in the study of the agglomeration economy of cities [19,32].

Population size and population density are the two main indicators of population agglomeration in urban agglomerations. It has been found that population size contributed significantly to economic growth in U.S. cities [33]. Furthermore, Duranton measured urban development in Colombia between 2008 and 2012 and found that a large population size resulted in a significant boost to labor output [34]. However, the relationship between population size and the economic growth of Chinese cities tends to be “inverted U-shaped” [35]. This is partly due to the fact that China’s mega-cities implement policies to control the size of building land and populations, and that infrastructure and public services cannot meet the demands of population growth [36]. Compared with population size, population density can better reflect the spatial agglomeration characteristics of urban areas and better measure the urban agglomeration economy. Earlier, Ciccone pointed out the important role of population density and found that every doubling of the population density in U.S. cities increased labor productivity by 6% [37]. Ciccone further selected data from 628 regions in five European countries and noted that a doubling of population density resulted in a 4.5% increase in regional economies [38]. Faberman used the U.S. Bureau of Statistics business micro-data and found that after controlling for geology, climate, and other factors, the coefficient of the population density’s effect on labor income is 3% [39]. Henderson found that population density has a significant positive impact on household income by measuring the urban economic density in African countries [40]. Chen confirmed the significant positive impact of population density on the economic growth of Chinese cities by constructing the urban growth model of the effect of population density on per capita urban land revenue, which could be a solution to the endogeneity problem [41]. However, there is no consensus on the significant positive impact of population density on economic growth in Chinese cities because Chinese cities have a higher population density than cities in other countries. Some scholars introduced the square term of population density into the income per capita model, and found that the impact of population density on China’s urban economic growth is characterized by an “inverted U” shape, in which growth is first promoted and then suppressed [42].

The impact of population density on economic growth also plays a role across cities/regions. Firstly, when integrating the spatial spillovers from neighboring regions, the local population density still contributes significantly to economic growth. Based on the significant positive impact of population density on the economic level in each region of five European countries, Ciccone constructed a theoretical formula for the integration of neighboring regions and the results showed that the positive impact of local population density remained unchanged [38]. Indeed, spatial econometric techniques have produced a significant improvement in the accuracy and objectivity of these types of work [43]. Secondly, there are obvious spatial spillover effects of population density in neighboring cities. The higher population and agglomeration levels of surrounding cities often contribute to
economic growth [38,44]. Zhang used spatial dynamic panel estimation and found that the agglomeration economy of neighboring cities had a significant promoting effect on local economic growth, with a coefficient of 0.14% [43]. Meijers measured the spatial structure of metropolitan areas in the United States and found that polycentric spatial structures can produce higher labor productivity by avoiding the diseconomy of agglomeration and enjoy spillover effects in the process of the agglomeration of different centers compared with monocentric structures [45]. Neighboring areas or more closely connected areas have a higher level of population density, which often has a certain spillover effect on the local area, prompting a greater inflow of population, capital, technology, etc., and academics define this process as the “borrowing size” [46]. Camagni analyzed the reasons for the faster economic growth of second-rank cities in Western Europe between 1995 and 2006 and found that second-rank cities can achieve their own rapid growth through urban networks and borrowing the size of surrounding large cities [47]. In essence, for Chinese urban agglomerations, the “borrowing size” is more likely to form within Chinese urban agglomerations due to the close connection between districts and counties [48]. However, the close connection also brings the “agglomeration shadow” to the areas around the big cities within the urban agglomerations. Chen found that the core city of Beijing–Tianjin–Hebei inhibited the development of the neighboring cities, and there exists a “poverty belt around Beijing and Tianjin” [49].

To summarize, empirical studies that choose to explore the spatial differences in economic growth within urban agglomerations at the district and county scale have become increasingly mature, and they believe that the “core-periphery” pattern is the basic spatial pattern of most urban agglomerations in China at present. However, there is no consensus on the conclusion that “the degree of economic disparity within Chinese urban agglomerations is decreasing year by year”, and economic disparities in inland areas, especially those involving cross-provincial urban agglomerations, are still mostly on the rise. In terms of the explanatory mechanism of spatial differences, the population agglomeration indicator represented by population density is a better measure of the agglomeration economic effect within urban agglomerations. However, the significant positive effect of population density on economic growth in Chinese cities still needs a lot of basic validation. The reason for this is that, firstly, the regression models that directly consider the effect of population density on GDP per capita mostly suffer from problems such as endogeneity. Su provided a solution to this problem through GMM estimation methods using a model that incorporates a first-order lagged term in the GDP per capita analysis [42]. Secondly, China’s statistical yearbooks cannot provide robust city/district/county construction land data for consecutive years. Chen extracted construction land data from nighttime lighting data, providing a reference for accurately obtaining population density indicators for consecutive years [41]. At the same time, the impact of population density on economic growth also plays a role between regions, but this work is still in its infancy. There is still a lack of basic research exploring the effect of the agglomeration economy that integrates the influence of factors such as the economy and population in surrounding regions. The hypothesis that “neighboring regions with higher levels of population density tend to have certain spillover effects on the local area” still needs to be tested. In essence, the idea of “borrowing size” provides a theoretical basis for the study of the economic effect of agglomeration between cities, while the spatial econometric techniques have greatly improved the scientific accuracy of relevant empirical research methods.

3. Methods and Data
3.1. Methods
3.1.1. Measurement Methods That Simultaneously Consider the Extent of Intra- and Inter-City Differences in Economic Growth

We draw on the “ratio-mean” method of GDP per capita adopted by Li to measure the degree of spatial differences in the economic growth of the Guanzhong Plain urban agglomeration at the district and county scales [50]. The total number of GDP per capita
ratios for the 89 districts and counties (given that the number of districts and counties within each city needs to be two or more when measuring the effects of spatial differences on GDP per capita, and that the Guanzhong Plain urban agglomeration only includes the XiFeng District in Qingyang City, we excluded Qingyang City, while the Yangling Demonstration Zone is included in Xianyang. Therefore, the number of districts and counties used in this method is 1 district less than the actual 90 districts and counties in the Guanzhong Plain urban agglomeration) in the Guanzhong Plain urban agglomeration is 3916, and the total number of intra-city differences in the nine prefectural-level cities is 416, of which 78 are in Xi’an City ($C^2_1 = 78$), 91 are in Xianyang City ($C^2_4 = 91$), 66 are in Baoji City ($C^2_6 = 66$), 6 are in Tongchuan City ($C^2_4 = 6$), 6 are in Shaanxi City ($C^2_6 = 6$), 55 are in Weinan City ($C^2_1 = 55$), 28 are in Linfen City ($C^2_2 = 28$), 55 are in Yuncheng City ($C^2_2 = 55$), 21 are in Tianshui City ($C^2_2 = 21$), and 10 are in Pingliang City ($C^2_2 = 10$); the total number of cross-city differences is 3500 ($C^2_3 + C^2_6 + C^2_5 + \ldots + C^2_{14}$). If the above samples are sorted in the order of intra-Xi’an, intra-Xianyang, intra-Baoji, intra-Tongchuan, intra- Shaanxi, intra-Weinan, intra-Linfen, intra-Yuncheng, intra-Tianshui, intra-Pingliang, and cross-city differences, the mean of the 3916 samples can be decomposed into Equation (1).

\[
\sum_{i=1}^{3916} \frac{y_i}{3916} = \frac{78}{3916} \sum_{i=1}^{3916} \frac{y_i}{3916} + \frac{169}{3916} \sum_{i=1}^{3916} \frac{y_i}{3916} + \frac{235}{3916} \sum_{i=1}^{3916} \frac{y_i}{3916} + \frac{241}{3916} \sum_{i=1}^{3916} \frac{y_i}{3916} + \frac{247}{3916} \sum_{i=1}^{3916} \frac{y_i}{3916} + \frac{302}{3916} \sum_{i=1}^{3916} \frac{y_i}{3916}
\]

\[
+ \frac{385}{3916} \sum_{i=331}^{3916} \frac{y_i}{3916} + \frac{406}{3916} \sum_{i=331}^{3916} \frac{y_i}{3916} + \frac{416}{3916} \sum_{i=331}^{3916} \frac{y_i}{3916} + \frac{407}{3916} \sum_{i=331}^{3916} \frac{y_i}{3916} + \frac{3916}{3916} \sum_{i=331}^{3916} \frac{y_i}{3916}
\]

where $y_i$ represents the ratio of GDP per capita in any two districts and counties, and the ratio between every two districts and counties can occur only once. The advantage of this measure is that it allows for a clear comparison of the differences in GDP per capita and its evolution within and between cities at the district and county scales.

### 3.1.2. Empirical Formula for the Impact of Population Density on the Urban Agglomeration’s Economic Growth

Ciccone constructed an empirical formula for measuring the impact of population density on regional economic growth [38]. First, it is assumed that the level of land-averaged output $Q_s/A_s$ in the region $s$ can be written as $Q_s/A_s = \Omega_s f(N, K_s, Q_s, A_s)$, where $\Omega_s$, $N$, $K_s$, and $A_s$ represent the region’s productivity level, labor force size, human capital, and capital stock, respectively, and $Q_s$ and $A_s$ represent the region’s total output and total area. Subsequently, on the assumption that returns to scale are constant and that labor and capital are in a spatial equilibrium, he proposed a basic model for the effect of population density on per capita output, that is $\log(Q_s/N_s) = \theta \log(N_s/A_s) + \phi \log(K_s/N_s) + \varphi \log H_k + D_{(\text{region})} + u_s$, where $\theta$, $\phi$, and $\varphi$ represent the coefficients of population density, capital stock per capita, and human capital, respectively, $D_{(\text{region})}$ is the regional dummy variable, and $u_s$ is the residual term. Finally, Ciccone constructed a measurement equation for the level of population output that incorporates the effects of the population density of neighboring regions; then, the equation can be written as $\log(Q_s/N_s) = \theta \log(N_s/A_s) + \phi \log(K_s/N_s) + \varphi \log H_k + \omega \log(Q_{sn}/A_{sn}) + D_{(\text{region})} + v_s$, where $\omega$ is the coefficient of influence of population density $Q_{sn}$ in the neighboring region $n$, and $v_s$ is the residual term.

Drawing on Ciccone’s measurement model [38], we chose to use population density to measure the degree of population density, and proposed that the basic formula for the population density of district and county $i$ within the urban agglomeration affecting GDP per capita in year $t$ is as shown in Equation (2):

\[
\ln y_{it} = \alpha \ln \text{Density}_{it} + \beta \ln \text{Population}_{it} + \gamma \ln H_{it} + \delta D_{(\text{region})} + \epsilon_{it}
\]

where the explained variable $y_{it}$ represents the GDP per capita of the district and county $i$ in the year $t$; the core explanatory variable $\text{Density}_{it}$ represents the population density; the control variables $k_{it}$, $H_{it}$, and $D_{(\text{region})}$ represent the capital stock per capita, the degree of human capital, and the district and county dummies, respectively; $\alpha$, $\beta$, and $\gamma$ denote
the coefficient of the population density, capital stock per capita, human capital, and the regional dummy variable, respectively; and \( \epsilon_{it} \) is the random perturbation term.

Since it has been found that the effect of population density on regional GDP per capita is mostly endogenous, we constructed a first-order dynamic distribution lag model of the effect of population density on GDP per capita, as shown in Equation (3):

\[
\ln y_{it} = \ln y_{i(t-1)} + \alpha \ln \text{Density}_{it} + \beta \ln k_{it} + \gamma \ln H_{it} + \delta D(\text{region})_{it} + \epsilon_{it}
\]

where \( y_{i(t-1)} \) denotes the GDP per capita of the last year in the district and county \( i \), which was added to control for unobserved factors interfering with the level of urban income at time \( t \).

Subsequently, we constructed a measurement model of the impact of population density on GDP per capita by integrating neighboring districts and counties. We mainly validate two questions, the first of which is whether population density in neighboring districts and counties has a spillover effect on local GDP per capita. For this reason, we drew on the idea of the “borrowing size” based on Equation (1), which means that regions close to large cities are more likely to receive the benefits brought about by the high population density in large cities. We added the dummy variable of “proximity high population size districts and counties” and the interaction term “\( \ln(\text{population density}) \times D(\text{proximity high population size districts and counties}) \)” to Equation (3), respectively, as shown in Equations (4) and (5):

\[
\ln y_{it} = \alpha \ln \text{Density}_{it} + \beta \ln k_{it} + \gamma \ln H_{it} + \kappa D(\text{Large})_{in,t} + \epsilon_{it}
\]

\[
\ln y_{it} = \alpha \ln \text{Density}_{it} + \beta \ln k_{it} + \gamma \ln H_{it} + \eta D(\text{Large})_{in,t} \times \ln \text{Density}_{it} + \epsilon_{it}
\]

where \( D(\text{Large})_{in,t} \) is a dummy variable for “surrounding districts with in the top 10% of population size”, \( \kappa \) denotes the coefficient of a district county which is surrounded by districts with a larger population size, and \( \eta \) denotes the coefficient of the interaction term between higher-population-size neighboring districts and the local population density. If \( \kappa \) and \( \eta \) are significantly positive, it indicates that the population density of the neighboring districts and counties has a positive spillover effect on the local economic growth; in contrast, if \( \kappa \) and \( \eta \) are significantly negative, it indicates that the population density of the neighboring districts and counties has a restraining effect on the local economic growth. In order to solve the problem of multicollinearity, Equations (4) and (5) exclude the district and county dummy variables while keeping the core and main control variables constant.

The second question to be verified is whether there is a change in the extent to which the population density in the region affects the local GDP per capita when incorporating the influence of neighboring counties. As shown in Equations (6)–(8), we drew on the techniques of spatial econometrics to construct formulas for the measurement of the population density effect of local districts when incorporating the influence of neighboring districts and counties. Equation (8) is able to corroborate the robustness of Equations (4) and (5).

\[
\ln y_{it} = \alpha \ln \text{Density}_{it} + \rho W \ln y_{it} + \beta \ln k_{it} + \gamma \ln H_{it} + \epsilon_{it}
\]

\[
\ln y_{it} = \alpha \ln \text{Density}_{it} + \beta \ln k_{it} + \gamma \ln H_{it} + u_{it}, \quad u_{it} = \lambda W \epsilon_{it} + \epsilon_{it}
\]

\[
\ln y_{it} = \alpha \ln \text{Density}_{it} + \beta \ln k_{it} + \gamma \ln H_{it} + \rho W \ln y_{it} + \alpha' W \ln \text{Density}_{it} + \beta' W \ln k_{it} + \gamma' W \ln H_{it} + \epsilon_{it}
\]

Equations (6)–(8) are formulas for measuring the population density effect of local districts and counties when incorporating the influence of neighboring districts and counties. Equation (6) is a spatial autoregression model (SAR), which indicates that the neighboring districts and counties directly affect the economic growth of the local districts and counties through spatial spillover effects; \( W \) and \( \rho \) denote the spatial weight matrix and the spatial lag term impact coefficients, respectively. Equation (7) is the spatial error model (SEM), which indicates that the neighboring districts and counties affect the economic growth of
the local districts and counties through the spatial dependence of the error term; $\lambda$ is the influence coefficient of the spatial error term. Equation (8) is the spatial Durbin model (SDM), which indicates that on the basis of the spatial autoregressive model and considers the influence of each explanatory variable of the neighboring districts and counties on the economic growth of the local district and counties through the effect of spatial spillover effects; $\alpha', \beta', \gamma'$ represent the coefficients of the influence of the population density, capital stock per capita, and human capital of the neighboring districts and counties on the GDP per capita of the local district and counties, respectively. Equation (8) can not only solve the problem of possible multiple covariances between the population density of neighboring regions and the local population density in Ciccone’s model [38], but it also can compare the local effect of population density with the indirect effect of the neighboring region by obtaining a more accurate coefficient of the influence of the population density of the neighboring region.

3.2. Data Sources

We chose the GDP per capita data from 2005 to 2020 to measure the economic level of 89 districts and counties in the urban agglomeration of the Guanzhong Plain. The GDP and resident population data were mainly derived from the statistical yearbooks of Shaanxi, Shanxi, and Gansu provinces, and the “Tabulation on the 2010 population census of the people’s republic of China by county” and “Tabulation on 2020 China population census by county” were selected to verify the accuracy of the permanent population data. Among them, the resident population of Yaodu District in Shanxi Province in 2005–2009 was nearly 20% less than that of the 2010 Census. Since this district did not have an administrative division adjustment in 2010, we used the interpolation method to revise the permanent population data of this district from 2005 to 2009.

Based on the population density measure proposed by Zhou [51], the core explanatory variable population density is equal to the resident population/built-up area of the district or county. Among them, the existing statistical yearbooks in China cannot provide robust built-up area data for consecutive years [41]. Therefore, based on nighttime lighting data [52] (nighttime lighting imagery data sources: http://ngdc.noaa.gov/eog (accessed on 29 November 2022)), we used the “Temporal and spatial normalization model” [41] to extract the built-up area at the county scale of the Guanzhong Plain urban agglomeration from 2005 to 2020 (Figure 1).

Figure 1. Extraction of land for construction in the Guanzhong Plain urban agglomeration, 2005–2020.
Of the control variables, capital stock data were obtained through the perpetual inventory method. Specifically, we used the formula $K_{i2005} = I_{i2005} \left( \frac{1 + g_i}{(1 + g_i + \delta)} \right)$ to calculate the capital stock of the 89 districts and counties in the base year of 2005, where $I_{i2005}$ is the fixed asset investment amount of district and county $i$ in 2005, $g_i$ is the GDP per capita growth rate of district and county $i$ in 2005–2006, and the depreciation rate $\delta$ is uniformly selected as 9.6%. Next, according to the formula $K_t = K_{(t-1)} + I_t - \delta K_{(t-1)}$, the capital stock data of each district and county from 2005 to 2020 were obtained, where $I_t$ is the total fixed asset investment in year $t$, and the data were derived from the statistical yearbooks of each province.

The data of hospitals and schools were based on crawling the POIs of hospitals and schools in the 89 districts and counties in the Gaode map, and querying each hospital or school one by one for the year of establishment, type, grade, and other information. Finally, the panel data of secondary schools, elementary schools, and the level 3 and level 2 hospitals in each district and county of the Guanzhong Plain urban agglomeration were obtained for each year from 2005 to 2020 (the data of key schools per capita in the control variables were also obtained using this method). The dummy variables “whether it has a train station” and “whether it has a high-speed rail station” were obtained from “China transport statistical Yearbook” and “Shannxi transportation statistical yearbook”. The spatial weight matrix was obtained using Geoda 1.14 based on the administrative boundaries according to the criterion of close proximity (proximity = 1, otherwise = 0).

4. Results

4.1. Characteristics of the Evolution of Spatial Differences in the Guanzhong Plain Urban Agglomeration

Firstly, we select the GDP per capita of each district and county in the Guanzhong Plain urban agglomeration in 2005, 2010, 2015, and 2020 to analyze the pattern of spatial differences in the economic growth of the Guanzhong Plain urban agglomeration. As shown in Figure 2, the Guanzhong Plain urban agglomeration had formed a “core-periphery” development pattern. The core was the main urban areas of Xi’an–Xianyang and Baoji, which was gradually spreading to the neighboring districts and counties within the three cities.

As shown in Figure 2a, the Guanzhong Plain urban agglomeration had formed a “core-periphery” pattern in 2005, in which the core was the main urban areas of Xi’an–Xianyang and Baoji. Although the GDP per capita of the “core area” was CNY 20,184.85 per person, the “periphery area” was only CNY 8063.76 per person. In fact, there are high-income districts and counties in the “periphery area” (e.g., Hejin) due to its rich coal resources and extraction industries. Figure 2b–d also show a spatial development pattern where the main urban areas of Xi’an–Xianyang and Baoji were gradually spreading to other districts and counties within these cities in 2010, 2015, and 2020. In 2005, the core area was only concentrated in the six districts of Xi’an and the municipal districts of Xianyang and Baoji. In the following 15 years, Chang’an District, Gaoling District, Xingping City, and Fengxian County, which are adjacent to the core area of Xi’an–Xianyang, all developed rapidly. For example, in the early 2000s, the Chang’an District of Xi’an obtained the continuous transfer of higher education resources from Yanta and other districts in the same city, which subsequently gathered talents, developed supporting industries, and enhanced the economic development in an all-around way.

Figure 3 further compares the degree of spatial differences in GDP per capita among the districts and counties of the Guanzhong Plain urban agglomeration from 2005 to 2020 according to Equation (1). The results show that the overall economic disparity (red line) in the Guanzhong Plain urban agglomeration is mainly attributed to the cross-city disparity (blue line), and their spatial disparity is generally on an increasing trend, while the economic disparity within each city (black line) is on a decreasing trend, especially since the implementation of the construction plan for the Guanzhong Plain urban agglomeration in 2018. Among them, the cross-city difference accounted for about 90% of the overall difference, and its ratio-mean value was still rising, indicating that the gap between the
“core area” and the “peripheral area” within the Guanzhong Plain urban agglomeration is continuing to widen at this stage. Within the cities, Xi’an, Xianyang, and Baoji had the greatest degree of intra-city variation, which corroborates the concentration of core areas in the economically developed regions of Xi’an, Xianyang, and Baoji. Shangluo, Tongchuan, and Pingliang had the smallest degree of intra-city variation, and their ratio-mean values also show a decreasing trend. Figure 3 confirms that the spatial evolution pattern of the “core area” of the Guanzhong Plain urban agglomeration is gradually spreading to the other districts and counties within these cities.

Figure 2. Patterns of spatial differences in the Guanzhong Plain urban agglomeration in 2005, 2010, 2015, and 2020.

Figure 3. Trends in the “ratio-mean” of GDP per capita by district and county in the Guanzhong Plain urban agglomeration, 2005–2020.
4.2. Impact of Population Density on Economic Growth within Districts and Counties

Table 1 shows the results of the panel regression analysis and its GMM estimation test using Equations (2) and (3) to analyze the impact of population density on the GDP per capita of each district and county in the Guanzhong Plain urban agglomeration from 2005 to 2020. The results show that population density had a significant and robust positive impact on GDP per capita in all districts and counties. The coefficient was approximately 0.06. This shows that population density can significantly promote the economic growth of the districts and counties within the urban agglomeration.

<table>
<thead>
<tr>
<th>Variables</th>
<th>Model 1 (FE)</th>
<th>Model 2 (FE)</th>
<th>Model 3 (FE)</th>
<th>Model 4 (FGLS)</th>
<th>Model 5 (GMM)</th>
<th>Model 6 (GMM)</th>
<th>Model 7 (GMM)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Ln(GDP_{t-1})</td>
<td>0.679 ***</td>
<td>0.598 ***</td>
<td>0.604 ***</td>
<td>(343.229)</td>
<td>(378.399)</td>
<td>(322.039)</td>
<td></td>
</tr>
<tr>
<td>Ln(population density)</td>
<td>0.004 **</td>
<td>0.069 ***</td>
<td>0.054 ***</td>
<td>(2.391)</td>
<td>(5.233)</td>
<td>(4.242)</td>
<td></td>
</tr>
<tr>
<td>Ln(capital stock per capita)</td>
<td>0.066 ***</td>
<td>0.003 **</td>
<td>0.057 ***</td>
<td>(12.565)</td>
<td>(8.910)</td>
<td>(5.101)</td>
<td></td>
</tr>
<tr>
<td>key school per capita</td>
<td>0.022 ***</td>
<td>0.046 ***</td>
<td>0.046 ***</td>
<td>(31.474)</td>
<td>(38.519)</td>
<td>(29.087)</td>
<td></td>
</tr>
<tr>
<td>D(municipal district)</td>
<td>2.955 ***</td>
<td>2.955 ***</td>
<td>2.955 ***</td>
<td>(8.395)</td>
<td>(8.395)</td>
<td>(8.395)</td>
<td></td>
</tr>
<tr>
<td>D(has train station)</td>
<td>0.243 ***</td>
<td>0.243 ***</td>
<td>0.243 ***</td>
<td>(10.306)</td>
<td>(10.306)</td>
<td>(10.306)</td>
<td></td>
</tr>
<tr>
<td>R²</td>
<td>0.126 ***</td>
<td>0.114 ***</td>
<td>0.222 ***</td>
<td>(13.882)</td>
<td>(12.772)</td>
<td>(12.772)</td>
<td></td>
</tr>
<tr>
<td>Sargan’s test p-value</td>
<td>0.976</td>
<td>0.979</td>
<td>0.973</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

T statistics in parentheses; ** p < 0.05, *** p < 0.01; FGLS estimation considers parameters that simultaneously overcome between-group heteroscedasticity and within-group autocorrelation.

Model 1 is the panel regression result, which considers population density as the only factor affecting GDP per capita. The \( p \)-value of the Hausman test was less than 0.1. We chose to use individual fixed effects. The coefficient of population density was positive and significant at a 1% level, which shows that population density had a significant positive impact on GDP per capita. We also added a quadratic term for population density to model 1; however, the quadratic term coefficient was not significant. Therefore, the significant positive effect of population density on GDP per capita was linear. Model 2 consists of a capital stock per capita element added to model 1 according to Formula (2). The results show that the coefficient of population density was significantly increased from 0.004 to 0.069, and it was still significant at the 1% level. Based on model 2, model 3 added the variable of key schools per capita to measure human capital. Model 4 further added the regional dummy variables. Since regional dummy variables do not vary over time, we chose the feasible generalized least squares estimation (FGLS) method to analyze panel data to control for possible heteroscedasticity and autocorrelation problems. The regression results for models 3 and 4 show that the effect of population density on GDP per capita remained significant at the 1% level. In order to test the robustness of the regression results of models 1–4 and to solve the endogeneity problem, according to Equation (3), we further used GMM estimation to measure the extent of the effect of population density when adding the lagged term of GDP per capita (see Models 5–7). The results show that the coefficient of population density on GDP per capita stabilized around 0.06 and remained significant at the 1% level. Meanwhile, the \( p \)-value of the Sargan test was greater than 0.1, so we cannot reject the hypothesis that instrumental variables obey an exogenous chi-square distribution. This verifies the rationality of the dynamic panel model selection.

There were significant spatial differences in population density and GDP per capita between municipal districts and neighboring counties and between accessibility and lack...
of accessibility, so are there also spatial differences in the impact of population density on GDP per capita? Table 2 adds the interaction of population density with the dummy variables “whether it is a municipal district”, “whether it has a train station”, and “whether it has a high-speed rail station”, respectively. The results show that the promotion effect of population density on GDP per capita was stronger in districts and counties that have a train station and are located in a municipal district. However, the regression result that municipal districts had a stronger population density effect was not robust.

Table 2. Spatial variation in the effect of population density on GDP per capita.

<table>
<thead>
<tr>
<th>Variables</th>
<th>Model 1</th>
<th>Model 2</th>
<th>Model 3</th>
<th>Model 4</th>
<th>Model 5</th>
<th>Model 6</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>(FE)</td>
<td>(FE)</td>
<td>(FE)</td>
<td>(GMM)</td>
<td>(GMM)</td>
<td>(GMM)</td>
</tr>
<tr>
<td>Ln(GDP&lt;sub&gt;t−1&lt;/sub&gt;)</td>
<td>0.605***</td>
<td>0.597***</td>
<td>0.542***</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(140.689)</td>
<td>(150.103)</td>
<td>(99.524)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Ln(population density)</td>
<td>0.040***</td>
<td>0.046***</td>
<td>0.058***</td>
<td>0.065***</td>
<td>0.057***</td>
<td>0.061***</td>
</tr>
<tr>
<td></td>
<td>(3.138)</td>
<td>(3.631)</td>
<td>(4.681)</td>
<td>(32.733)</td>
<td>(33.371)</td>
<td>(35.421)</td>
</tr>
<tr>
<td>Ln(population density) × D(municipal district)</td>
<td>0.045***</td>
<td></td>
<td></td>
<td>−0.024***</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(6.021)</td>
<td></td>
<td></td>
<td>(−10.273)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Ln(population density) × D(has train station)</td>
<td>0.029***</td>
<td></td>
<td></td>
<td></td>
<td>0.002***</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(6.450)</td>
<td></td>
<td></td>
<td></td>
<td>(4.692)</td>
<td></td>
</tr>
<tr>
<td>Ln(population density) × D(has high-speed rail station)</td>
<td></td>
<td>−0.031***</td>
<td></td>
<td></td>
<td>−0.029***</td>
<td>−0.029***</td>
</tr>
<tr>
<td></td>
<td></td>
<td>(−8.271)</td>
<td></td>
<td></td>
<td>(−31.287)</td>
<td></td>
</tr>
<tr>
<td>Ln(capital stock per capita)</td>
<td>0.110***</td>
<td>0.112***</td>
<td>0.131***</td>
<td>0.048***</td>
<td>0.046***</td>
<td>0.086***</td>
</tr>
<tr>
<td>key school per capita</td>
<td>3.550***</td>
<td>4.470***</td>
<td>4.575***</td>
<td>4.928***</td>
<td>3.818***</td>
<td>4.062***</td>
</tr>
<tr>
<td>constant</td>
<td>8.282***</td>
<td>8.139***</td>
<td>8.190***</td>
<td>2.838***</td>
<td>2.946***</td>
<td>3.396***</td>
</tr>
<tr>
<td></td>
<td>(70.470)</td>
<td>(69.084)</td>
<td>(70.564)</td>
<td>(93.440)</td>
<td>(83.939)</td>
<td>(78.621)</td>
</tr>
<tr>
<td>N</td>
<td>1440</td>
<td>1440</td>
<td>1440</td>
<td>1350</td>
<td>1350</td>
<td>1350</td>
</tr>
<tr>
<td>R²</td>
<td>0.4817</td>
<td>0.4788</td>
<td>0.4538</td>
<td>0.98</td>
<td>0.978</td>
<td>0.982</td>
</tr>
</tbody>
</table>

T statistics in parentheses; *** p < 0.01.

Models 1–3 show the results of the fixed effects regressions, which report the interaction terms of the three dummy variables with population density on the impact on GDP per capita, respectively. The results state that districts that were municipal districts and districts with train stations had increased positive coefficients of population density on GDP per capita by 0.045 and 0.029, respectively, compared to other districts. The effect of population density on GDP per capita in counties with high-speed rail stations was significantly positive, but the coefficient value was lower than that of other counties by 0.031. The possible reason for this is that high-speed rail stations are mostly built in the more remote suburbs. In addition, the construction of the high-speed rail stations was relatively late, and it will take time for it to facilitate increases in population density and economic growth. Models 4–6 further measure the robustness of models 1–3 based on GMM estimation, which added the lagged term of GDP per capita. Model 4 shows that the interaction term between “whether it is a municipal district” and population density was still significant at the 1% level, but with the opposite sign of model 1. This suggests that the regression result from model 1 was not robust. The results of the interaction terms for models 5 and 6 were generally consistent with the degree of the effects of models 2 and 3, verifying the robustness of models 2 and 3.

4.3. Impact of Population Density on Economic Growth by Incorporating the Spillover of Effects from Neighboring Districts and Counties

Table 3 shows the regression results of the impact of population density on economic growth when incorporating the spillover effects of neighboring districts and counties. We not only used Equations (4) and (5) to verify whether the agglomeration economy of the neighboring districts and counties had a spillover effect on the local GDP per capita, but also adopted Equations (6)–(8) to analyze the impact of local population density on GDP per capita when integrating the influence of the neighboring districts and counties. The
regression results of the two types of models were basically consistent, indicating that the model setup in this study is reasonable. The results show that the spatial agglomeration of economic and population factors in neighboring districts and counties had a positive spillover effect on the local economic level. Meanwhile, when incorporating the spillover effects of neighboring districts and counties, the impact of local population density on local economic growth remained significantly positive.

Table 3. Impact of population density on economic growth when incorporating spillovers from neighboring counties.

<table>
<thead>
<tr>
<th>Variables</th>
<th>Model 1 (FGLS)</th>
<th>Model 2 (FE)</th>
<th>Model 3 (SAR)</th>
<th>Model 4 (SEM)</th>
<th>Model 5 (SDM)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Ln(population density)</td>
<td>0.123 ***</td>
<td>0.051 ***</td>
<td>0.030 ***</td>
<td>0.024 **</td>
<td>0.009</td>
</tr>
<tr>
<td></td>
<td>(23.496)</td>
<td>(4.137)</td>
<td>(2.794)</td>
<td>(1.962)</td>
<td>(0.728)</td>
</tr>
<tr>
<td>Ln(capital stock per capita)</td>
<td>0.269 ***</td>
<td>0.115 ***</td>
<td>0.067 ***</td>
<td>0.130 ***</td>
<td>0.338 ***</td>
</tr>
<tr>
<td></td>
<td>(49.887)</td>
<td>(13.557)</td>
<td>(8.778)</td>
<td>(11.132)</td>
<td>(16.674)</td>
</tr>
<tr>
<td>key school per capita</td>
<td>3.695 ***</td>
<td>4.363 ***</td>
<td>3.326 ***</td>
<td>3.802 ***</td>
<td>2.955 ***</td>
</tr>
<tr>
<td>D(proximity high population size districts and counties)</td>
<td>0.027 *</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Ln(population density) × D(proximity high population size districts and counties)</td>
<td>0.019 ***</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(1.685)</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>W_Ln(population density)</td>
<td></td>
<td></td>
<td></td>
<td>0.021</td>
<td>(1.252)</td>
</tr>
<tr>
<td>W_Ln(capital stock per capita)</td>
<td></td>
<td></td>
<td></td>
<td>−0.286 ***</td>
<td>(−13.101)</td>
</tr>
<tr>
<td>W_key school per capita</td>
<td></td>
<td></td>
<td></td>
<td>0.799</td>
<td>(0.940)</td>
</tr>
<tr>
<td>ρ</td>
<td>0.456 ***</td>
<td></td>
<td></td>
<td>0.447 ***</td>
<td>(17.210)</td>
</tr>
<tr>
<td></td>
<td>(17.521)</td>
<td></td>
<td></td>
<td>(17.201)</td>
<td></td>
</tr>
<tr>
<td>λ</td>
<td>0.533 ***</td>
<td></td>
<td></td>
<td>0.533 ***</td>
<td>(18.210)</td>
</tr>
<tr>
<td></td>
<td>(18.210)</td>
<td></td>
<td></td>
<td>(18.210)</td>
<td></td>
</tr>
<tr>
<td>constant</td>
<td>7.405 ***</td>
<td>8.218 ***</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(156.138)</td>
<td>(72.273)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>R²</td>
<td>0.433</td>
<td>0.797</td>
<td>0.835</td>
<td>0.795</td>
<td></td>
</tr>
<tr>
<td>Wald test</td>
<td>3816.67 ***</td>
<td></td>
<td></td>
<td>177.622</td>
<td>193.6127</td>
</tr>
<tr>
<td>Log L</td>
<td></td>
<td></td>
<td></td>
<td>276.2383</td>
<td></td>
</tr>
</tbody>
</table>

T statistics in parentheses; * p < 0.1, ** p < 0.05, *** p < 0.01. The Hausman statistic for the SEM model was 150.41 and the probability value was 0.00, which caused us to reject the original hypothesis. Thus, the individual fixed effects model was used.

Models 1 and 2 show the regression results of adding the dummy variable of “proximity high population size districts and counties” and the interaction term “Ln(population density) × D(proximity high population size districts and counties)” one at a time. The results show that the dummy variable “proximity high population size districts and counties” and its interaction term with population density had a significant positive effect on GDP per capita, while the extent of the effect of population density and other factors remained unchanged. This shows that the population density of neighboring districts and counties had a positive spillover effect on local GDP per capita. Population density more strongly promoted the local GDP per capita in districts with “proximity high population sizes” than in districts “not proximity high population sizes”. Models 3 and 4 show the estimation results of the spatial autoregressive model (SAR) and spatial error model (SEM). The global Moran’I statistic for GDP per capita for the years 2005, 2010, 2015, and 2020 were 0.47, 0.49, 0.5, and 0.47, which were all significant at the 1% level. On the basis that variables such as population density were significantly positive and robust, the coefficient values of the spatial autocorrelation coefficient ρ and the spatial error term coefficient λ were 0.46 and 0.53, which were both significant at the 1% level. This indicates that the economic level of proximal districts and counties had a significant positive impact on local GDP per capita, whether through direct spatial spillovers or spatial spillovers of error terms. Model 5 further select the spatial Durbin model (SDM) to measure the spatial autocorrelation coefficient ρ and the spatial spillover effect of the core explanatory variables at the same time.
The results show that the spatial autocorrelation coefficient $\rho$ was still significantly positive and stabilized at 0.45. The coefficient of population density in the neighboring districts and counties was 0.021, which was not significant at the 10% level. But its t-value was 1.25, which is significant at the 10% level. This indicates that the population density of the neighboring districts and counties also positively contributed to the local GDP per capita. Taken together, the population size, economic level, and population density of neighboring districts and counties all had significant positive spillover effects on local GDP per capita. Meanwhile, when incorporating the spillover effects of proximal districts and counties, the impact of local population density on economic growth remained significantly positive.

5. Conclusions and Discussion

Through measuring the spatial differences in economic growth of the Guanzhong Plain urban agglomeration from 2005 to 2020, this study constructed an empirical formula for the impact of population density on the urban agglomeration's economic growth that takes into account the roles of intra- and inter-city interactions. Then, we analyzed the impact of population density on economic growth within the urban agglomeration, as well as the extent of the impact of population density on economic growth when incorporating spillover effects from neighboring districts and counties. The innovations of this study include two aspects: firstly, we constructed an empirical formula for the impact of population density on the urban agglomeration's economic growth that takes into account the roles of intra- and inter-city interactions by adopting the idea of “borrowing size” and the spatial panel econometric method, using the Guanzhong Plain urban agglomeration as an example to validate the reasonableness of the empirical formula. Secondly, based on nighttime light images, we obtained the urban construction land area data of 90 districts and counties in the Guanzhong Plain urban agglomeration of China from 2005 to 2020 by using the “temporal and spatial normalization method”. This solves the problem that the existing statistical data cannot accurately obtain the urban construction land area for consecutive years.

From the empirical results, we first found that, from 2005 to 2020, the Guanzhong Plain urban agglomeration had formed a “core-periphery” development pattern. The core of the development is the main urban areas of Xi’an–Xianyang and Baoji, and it gradually spread to the neighboring districts and counties of these three cities. From a static perspective, it is basically consistent with the spatial pattern of economic growth in other countries around the world and the eastern coastal urban agglomeration of China [4,19]; the Guanzhong Plain urban agglomeration in western China presents a standard “core—periphery” spatial characteristic. However, in terms of dynamic development, compared with Hao [13] and Liu [20] on the spatial development pattern of the Guanzhong Plain urban agglomeration before and in 2010, the Guanzhong Plain urban agglomeration developed from a single center with the main urban area of Xi’an as the core to a polycentric development model with the main urban areas of Xi’an–Xianyang and Baoji as the core. It can be seen that the cities of the second- and third-order population sizes of the Guanzhong Plain urban agglomeration have developed rapidly [23], and this result basically follows the spatial development model of urban agglomerations in developed countries and eastern China, from monocentric to polycentric [17,21]. Secondly, population density can significantly promote the economic growth of the districts and counties within the urban agglomeration, with a coefficient of approximately 0.06. When we used GMM estimation to measure the effect of population density with the addition of the lagged term of GDP per capita, the magnitude of its effect remained robust. This result is basically consistent with the current research conclusions on urban development in the United States, Europe, and Africa [38–40]. In addition, in order to verify the “inverted U” model, in which population density first promotes and then suppresses the economic growth of urban agglomerations [42], we added the squared term of population density to the explanatory variables of the basic model and found that the population density feature was still significant, but its squared term was not significant, and the GMM estimation results were the same. This indicated
that the promotion effect of population density within the urban agglomerations of inland China was linear. Thirdly, the spatial agglomeration of economic and demographic factors in neighboring counties had a positive spillover effect on the local economy, while the significantly positive impact of population density on economic growth remained unchanged when it was integrated into the spillover effect of neighboring counties. In order to analyze the changes in the degree of local population density effects when integrating the influence of neighboring districts and counties, we simultaneously added local and surrounding population density factors which were used by Ciccone [38] to discuss five European countries; we also drew on the work of Zhang [43] and adopted spatial econometrics to measure the effect of urban population density. The results were basically consistent with the above studies, indicating that our model setting is reasonable and robust. In analyzing the impact of population agglomeration in surrounding districts and counties, our research conclusion supports the view that “borrowing size”, that is, areas with more economic and population agglomeration, can bring benefits to surrounding areas [46]. In fact, the phenomenon of polycentric spatial structures in the United States [45] and the rapid growth of second-rank cities in Europe [47] both verify the universality of “borrowing size”. In addition, the phenomenon of “agglomeration shadow” in the Beijing–Tianjin–Hebei urban agglomeration in China [49] did not occur in the Guanzhong Plain urban agglomeration.

According to the research conclusion, we put forward two policy recommendations. Firstly, we should continue to promote regional development policies of spatial agglomeration and intensive land planning. The conclusion of this study shows that population density has a significant and stable effect on the economic growth of urban agglomerations. However, China’s western region has long faced the phenomenon of the allometric growth of urbanization, where land urbanization is greater than population urbanization, and there are problems such as a large amount of idle construction land and low space utilization. To this end, urban and rural construction should take strengthening the stock planning of land potential as the main goal, and promote the intensive development of industry and service industries. Secondly, we should strengthen the construction of industrial chains and road networks within urban agglomerations, and deepen the network connections between districts and counties. This study found that the spatial agglomeration of economic, population, and other factors can produce benign spatial spillover effects. Strengthening the network connections between districts and counties through industrial cooperation and road network construction not only reduces the cost of spatial spillover in neighboring districts and counties, but also conforms to the new concept of network construction to promote common development between cities [22]. To this end, local governments need to strengthen the integration of industrial chains in urban agglomerations on the one hand, and improve the construction of road networks such as inter-city highways and railways on the other hand. It should be pointed out that this study also found that the construction of high-speed rails has not yet promoted economic development in the Guanzhong Plain urban agglomeration. The possible reason for this is that most high-speed rail stations in western China are located in remote areas far from the economic center, and the surrounding industries and business districts are still not perfect. Therefore, it is necessary to effectively utilize the network-driven effect of high-speed rails by continuing to promote the planning and construction of industries or business districts around high-speed rail stations [53].

We only used the Guanzhong Plain urban agglomeration as a case study to explore the impact of population agglomeration on the economic growth of urban agglomerations. However, due to the differences in climate, topography, history, and other aspects in China, and the obvious differences in population agglomeration patterns between different urban agglomerations, the Guanzhong Plain urban agglomeration cannot fully represent the inland urban agglomerations of China. To this end, we still need to carry out comparative research on multiple urban agglomerations to identify the commonalities and differences between population agglomeration and economic growth models among different urban agglomerations. On the other hand, we found that since 2018, the economic spatial dif-
ferences in the Guanzhong Plain urban agglomeration have been obvious, but this study did not explore this finding in depth. In reality, 2018 is a period of transition for policy making in the Guanzhong Plain urban agglomeration, that is, from the “Guanzhong City Agglomeration” that only includes only the Guanzhong region of Shaanxi Province to the “Guanzhong Plain Urban Agglomeration”, which includes the three provinces of Shaanxi, Shanxi, and Gansu. Therefore, whether the policy’s improvement reduces the economic differences in urban agglomerations can become another future research direction. In addition, the global environment has experienced ups and downs in recent years, especially due to the global COVID-19 epidemic. Although the COVID-19 epidemic has basically been controlled, people’s bottom-line thinking from the normalization of epidemic prevention and control will continue for many years. In the post-epidemic era of the full resumption of work and production, how to perfectly integrate the spatial agglomeration construction mode of urban agglomeration with resilient city construction in response to emergencies will be a research topic of great significance.


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