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The impact of urban polycentralization and scale expansion on economic efficiency: evidence from Chinese cities

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Introduction: This study investigates the effects of urban polycentricity and city size on total factor productivity (TFP) in Chinese cities.

Methods: Using high-resolution population distribution data from Landscan and applying instrumental variable (IV) estimation to address endogeneity concerns, we construct a novel measure of urban polycentricity.

Results: Our findings show that while expanding city size enhances TFP through increased economies of scale, greater urban polycentricity negatively affects productivity by weakening agglomeration economies and innovation spillovers.

Discussion: The analysis suggests that polycentricity reduces the concentration of economic activities, which hampers knowledge diffusion and innovation, leading to lower productivity. Additionally, we identify the optimal city size for maximizing TFP, where excessive urban growth beyond a certain point becomes counterproductive.

KEYWORDS

total factor productivity (TFP), polycentricity, agglomeration effect, City size, innovation spillover, China

1 Introduction

With the fast advancement of urbanization, changes in urban spatial structure have emerged as a key factor influencing urban economic growth and development (Anas et al., 1998; Liu et al., 2020; Dadashpoor and Malekzadeh, 2020). Urban spatial structure not only governs the distribution and layout of functional sectors inside a city, but it also has a significant impact on resource allocation (Zhu et al., 2018), industrial development (Liu et al., 2021), and manufacturing efficiency (Yu et al., 2019). In recent years, scientists have focused on the significance of urban agglomeration effects in fostering economic development, particularly total factor productivity (TFP), a key indicator of urban economic efficiency (Thisse, 2018; Liu et al., 2024a). As the world's largest developing country, China's complexity of urbanization and diversity of urban spatial organization make this issue especially pressing. Changes in urban spatial organization, especially polycentric growth trends, are likely to have significant impacts on regional economic productivity and therefore deserve further study.

In China's urbanization process, many scholars have begun to pay attention to the formation and development of urban polycentricity (Liu et al., 2018; Liu et al., 2016; Yue et al., 2019). Traditional urban planning emphasizes centralized development, but as urban agglomerations expand, polycentric spatial forms have gained popularity. Existing research primarily focuses on the relationship between city size, agglomeration effects, and economic outcomes such as GDP growth and employment distribution. However, few studies have systematically explored the impact of urban polycentricity on total factor productivity (TFP), a comprehensive measure of economic efficiency. Moreover, the mechanisms through which polycentric structures influence TFP—such as knowledge spillovers, innovation, and resource allocation—remain underexplored. These gaps limit our understanding of the costs and benefits of polycentric urban development, particularly in the context of developing countries.

This study aims to address these gaps by examining the impact of urban polycentricity on TFP and uncovering the underlying mechanisms. We investigate whether polycentricity enhances or hinders TFP, how this relationship varies across cities with different characteristics (e.g., population density, geographic location), and what policy implications can be drawn for optimizing urban spatial structures. By integrating theoretical insights with empirical analysis, our research not only contributes to the academic debate on urban planning and economic efficiency but also provides practical guidance for policymakers in developing countries facing similar urbanization challenges.

The primary goal of this research is to investigate the impact of urban polycentricity on regional total factor productivity and its mechanism of action through the lens of urban spatial structure and scale. First, using the *Landscan* high precision population distribution database, this paper quantitatively examines the polycentricity distribution level of Chinese cities. This dataset can provide accurate and thorough population distribution statistics, allowing for a more scientific approach to analyzing urban spatial structure. Second, this research employs Chinese prefecture-level city data from 2010 to 2019 and a variety of econometric models to investigate the impact of urban spatial organization on regional total factor productivity. The relationship between urban spatial structure, city size, and total factor productivity is examined using several econometric frameworks, and the underlying mechanism of action is investigated.

This article's empirical result reveal that urban polycentric structure has a considerable negative impact on regional TFP, whereas city size growth promotes TFP improvement. Specifically, even after controlling for city and year fixed effects, the coefficient of urban polycentricity remains negative, indicating that the polycentric structure reduces the city's TFP, whereas increasing city size increases TFP. Further investigation revealed that when city size was introduced, the absolute value of the polycentric effect was marginally reduced, indicating that city size mitigated the detrimental impact of polycentricity to some extent. Both the robustness test and the heterogeneity analysis results show that polycentricity in coastal cities has a more significant negative impact on TFP, while urban scale expansion has a positive impact on TFP, especially in megacities. Furthermore, urban polycentricity limits the city's TFP growth by increasing the geographical distance between centers, reducing innovation output, and diminishing innovation spillover effects.

The marginal contributions of this paper are reflected in the following aspects:First, building on previous research, this paper provides a comprehensive theoretical and empirical analysis of the impact of urban spatial structure on total factor productivity (TFP). By exploring the mechanisms linking urban polycentricity and TFP—such as knowledge spillovers, innovation, and resource allocation—we offer new insights into how spatial organization influences economic efficiency. This contributes to the literature by addressing a critical gap in understanding the productivity implications of polycentric urban development.

Second, this paper employs high-precision data to scientifically measure population distribution and urban spatial structure. We introduce innovative metrics for quantifying polycentricity, which not only enhance the accuracy of spatial structure measurement but also improve the identification of its impact on regional TFP. This methodological advancement provides a robust foundation for future research in this field.

Third, while investigating the impact of urban polycentricity on TFP, this paper explicitly considers the urban scale effect and addresses potential endogeneity issues through rigorous econometric models. By conducting nationwide causal inference, we reduce estimation bias and provide more reliable empirical evidence. This approach overcomes the limitations of existing studies, which often overlook endogeneity and focus narrowly on the economic benefits of spatial structure, thereby offering policymakers a more nuanced and actionable understanding of urban planning strategies.

The remainder of this paper is organized as follows: Section 2 presents the theoretical analysis and research hypotheses. Section 3 primarily describes the main data and empirical model used in this study. Section 4 analyzes the empirical results, and Section 5 presents the conclusions of this paper.

2 Theoretical analysis and research hypothesis

2.1 Polycentralization and economic agglomeration effect

In recent years, academics have paid close attention to the relationship between urban spatial structure and economic construction results (Walker, 2018; Zhang et al., 2020; Long and Huang, 2019). Urban spatial structure typically refers to the spatial distribution of different functional areas within a city. This structure has significant implications for the city's economic development and productivity. Early research has shown that the shape of urban spatial structure is strongly related to economic growth, particularly in terms of resource allocation (Guo et al., 2020), labor market (Rosenthal and Strange, 2020), and industrial distribution (Xu and Jiao, 2021), all of which have a significant impact on productivity. For example, Chinitz (1961) observed that the diversity and agglomeration effect of urban space promote interaction and knowledge spillover between industries, thereby increasing overall productivity. Glaeser (2011) emphasized that cities' agglomeration effect can effectively promote innovation, resource flow, and labor market efficiency, all of which contribute to city economic growth. Duranton and Puga (2004) proposed that the urban space's division of labor effect is important at various stages of development. The alternation of the agglomeration and dispersion effects of cities will have an impact on industrial structure and resource allocation, thereby influencing the quality and speed of economic growth.

Especially in China, the rapid advancement of urbanization has brought about large-scale urban expansion (Wei and Ye, 2014; Ding et al., 2024). In order to achieve short-term economic development goals, many cities have promoted GDP growth by expanding city size and building infrastructure, while ignoring production efficiency and technological progress. Overreliance on land and capital inputs for economic growth frequently results in a lag in total factor productivity, and may even exacerbate resource waste and environmental burden (Wolff, 1991; Isaksson, 2007; Li et al., 2021). As a result, relying solely on traditional economic indicators to measure urban development while ignoring total factor productivity may not accurately reflect the true nature of urban development. Improving total factor productivity, particularly in terms of spatial structure and city size expansion, is a critical issue in China's urban development (Liu et al., 2024b).

However, despite the importance of urban spatial structure in economic development, few people have noticed that the polycentric structure that emerges gradually during the urbanization process may have a negative impact on the improvement of total factor productivity. The polycentric spatial structure refers to the process by which originally concentrated urban functions and economic activities are dispersed across multiple regions or "sub-centers" as the city expands (Roca Cladera et al., 2009; Yu et al., 2022). Although this shift has alleviated the over-concentration of resources in urban centers to some extent, it may also bring a series of negative consequences, especially challenges to productivity improvement (Derudder et al., 2021; Wang et al., 2019).

The effect of urban polycentricity on agglomeration and TFP is complex and multifaceted. First, urban polycentricity frequently results in decentralized resource allocation, which weakens the city's agglomeration effect (Dadashpoor and Yousefi, 2018; Chen et al., 2021). The agglomeration effect is a significant advantage of urban spatial structure because it promotes interaction between industries, technological innovation, and knowledge spillover, ultimately improving TFP. However, a polycentric structure frequently results in relative isolation between multiple functional areas, affecting resource allocation efficiency and technology diffusion. Ellison et al. (2010), for example, noted that an overly dispersed spatial structure can stifle industrial agglomeration and innovation activities, resulting in a decrease in overall productivity. It is difficult for resources and knowledge to flow fully across polycentricity, undermining the mechanism of technology spillover and preventing the city's innovation potential from being realized. This is in stark contrast to the centralized urban structure, which achieves efficient resource utilization and technology diffusion through agglomeration effects, resulting in increased productivity (Duranton and Puga, 2004).

Second, polycentricity can raise the cost of infrastructure construction and disrupt regional coordination (Escaleras and Calcagno, 2018; Frank and Martínez-Vázquez, 2015). In a single-center city, the concentration of economic activities usually reduces the duplication of infrastructure construction and transportation costs, whereas in a polycentric city, the cost of infrastructure construction and operation often rises dramatically (David and Kilani, 2022; Sweet et al., 2017). Furthermore, poor transportation and information exchange between the city's various centers may result in inefficient organization of overall economic activities, affecting productivity improvement. Henderson (2000) proposed that the polycentric structure would result in duplicate resource allocation and increased coordination and management costs, affecting the city's overall productivity. Specifically, the independent development of each sub-center may result in redundancy in infrastructure construction, increasing the fiscal burden and decreasing the city's overall operational efficiency.

With China's rapid urbanization, many large cities have gradually implemented a multi-center strategy, attempting to relieve pressure on the central city by decentralizing urban functions. However, this transformation process may present numerous challenges. Although multi-center can alleviate traffic congestion and overexploitation of land resources in the short term, a lack of effective policy coordination and infrastructure construction may prevent it from effectively promoting technological innovation and industrial upgrading, resulting in a decrease in productivity (Short and Kopp, 2005; Koppenjan and Enserink, 2009). For example, Su et al. (2017) discovered that in many large Chinese cities, despite the implementation of a multi-center strategy, a lack of effective spatial planning and regional coordination has resulted in inefficient productivity improvement and insufficient innovation capabilities. The multi-center structure may lead to the break of the industrial chain between different regions, reduce the synergy effect, and thus affect the total factor productivity of the city (Ding et al., 2022).

Polycentricity, particularly in small and medium-sized cities, can exacerbate spatial fragmentation and result in inefficient integration of economic activities (Dadashpoor and Yousefi, 2018). The relative independence of multiple economic functional areas prevents cities from forming a strong economic agglomeration effect similar to a monocentric structure, which not only affects technological innovation but also reduces labor and capital flow efficiency (Fujita et al., 1999). In these cities, an overly dispersed spatial layout may complicate industrial coordination, impeding productivity improvement and economic structure optimization (Ter Wal and Boschma, 2011).

Although the existing literature has explored the relationship between city size, spatial structure and innovation spillover effects, there are still several research gaps. First, the research on urban polycentricity and innovation spillover effects is relatively limited, especially the empirical research on Chinese cities is relatively scarce. Existing studies mostly focus on the economic effects of a single city center, and lack in-depth discussion on the specific mechanism of polycentricity and its inhibitory effect on innovation spillover effects. Second, the existing literature mainly stays at the theoretical level for the impact of city size on TFP, and most of the research focuses on cases in developed countries, lacking a systematic analysis of the impact of city size in the specific context of Chinese cities. In addition, although polycentricity can alleviate the congestion problem of large cities and optimize spatial layout, it may also bring about negative effects such as the dispersion of innovation resources, duplicate infrastructure construction and insufficient coordination between cities, thereby inhibiting the growth of urban productivity. Therefore, based on the goal of improving TFP, the polycentric transformation of urban spatial structure needs to be carefully considered. This study fills these gaps, systematically explores the dual impact of polycentricity and city size on TFP in Chinese cities, and combines multiple case empirical analysis to deeply reveal the specific mechanism of spatial structure on innovation and productivity.

2.2 Research hypothesis

The agglomeration effect of urban spatial structure is widely regarded as a key mechanism to promote economic growth and improve total factor productivity (TFP). Duranton and Puga (2004) pointed out that urban agglomeration not only promotes the flow of labor and capital, but also enhances the spillover effect of knowledge and improves innovation capabilities, thereby promoting productivity growth. In a monocentric urban structure, all economic activities and resources are relatively concentrated, which can improve the overall production efficiency of the city through a high degree of resource integration, technology diffusion and industrial cooperation (Ning et al., 2016; Zhang et al., 2022; Liang and Lu, 2019). However, when the urban spatial structure turns to polycentricity, the dispersion of multiple functional areas often leads to inefficient resource allocation and limited knowledge spillover, which may inhibit technological innovation and productivity improvement (Ellison et al., 2010). Therefore, the polycentricity of urban space may reduce the agglomeration effect, thereby having an adverse impact on total factor productivity.

Based on the above theoretical analysis, when the urban spatial structure tends to be polycentric, the relative isolation between multiple regions and functional areas will lead to the obstruction of resource flow and the weakening of synergy (Deng et al., 2024). This spatial structural transformation may reduce the spillover effect of technological innovation and cooperation between industries, thereby inhibiting the improvement of total factor productivity. Therefore, this study proposes the hypothesis:

Hypothesis 1. The trend of polycentric urban spatial structure will have a negative impact on regional total factor productivity.

A large body of literature shows that there is generally a positive relationship between city size and TFP. Glaeser (1961) pointed out that the expansion of urban size helps to promote technological innovation, labor mobility and efficient allocation of capital, and these factors jointly promote productivity improvements. In larger cities, agglomeration effects are usually more significant, with more frequent flows of resources and information, which in turn promotes innovation and technological progress (Carlino and Kerr, 2015; De Groot et al., 2009). At the same time, the economic activities in larger cities tend to be more diversified and the synergy effects between industries are more significant, which creates favorable conditions for the improvement of total factor productivity (Duranton and Puga, 2004). However, although urban size expansion usually brings economic benefits and productivity improvements, in the context of polycentralization, over-dispersed spatial layout may inhibit some synergy effects, especially in cities with smaller population sizes, which may lead to inefficiencies loss. Therefore, larger cities may mitigate the negative impacts of polycentric structures to some extent, but will still experience some productivity losses overall.

Combining the impact of city size and polycentric structure, it can be hypothesized that in larger cities, the agglomeration effect brought by city size can alleviate the negative impact of polycentricity to a certain extent, especially in larger cities with larger populations. In large cities, the flow of resources and knowledge between polycentric nodes is relatively smooth, and the synergy effect is more significant. However, despite this, further dispersion of space may still bring some efficiency losses. Therefore, this study hypothesizes.

Hypothesis 2. As the size of a city increases, its regional TFP gradually increases. For cities with larger populations, the adverse impact of polycenters on urban TFP creation will be weakened, but overall it will still bring some efficiency losses.

Changes in urban spatial structure are not only reflected in spatial distribution, but also involve the physical distance between different regions and the intensity of economic activity connections. Fujita et al. (1999) pointed out that urban polycentricity may lead to the dispersion of economic activities between different regions of the city. This dispersion will not only increase the transportation and information transmission costs between regions, but also weaken the innovation benefit spillover between regions. As the distance from the center increases, the effects of innovation and technological spillover will gradually weaken, and the cooperation and synergy between regions will also be affected (Henderson, 2000). Therefore, in theory, with the polycentricity of urban spatial structure, the increase in the distance between centers will lead to a decline in the spillover effect of knowledge and technology, thereby affecting the improvement of regional total factor productivity (Li and Du, 2022; Ahlfeldt and Wendland, 2013; Zambon et al., 2017).

By increasing the physical distance between centers and decreasing the spillover effect of innovation benefits, the polycentricity of urban spatial structure will impede technological advancement and productivity improvement, according to the theoretical analysis presented above. The growth of total factor productivity will be impacted by the limited spillover effect of innovation, particularly when there is a lack of cooperation and information flow amongst several sub-centers. Thus, this study makes the following hypothesis:

Hypothesis 3. Urban polycentricity may have a negative impact on regional TFP by reducing the spillover of innovation benefits and extending the distance between centers.

3 Empirical model and data

3.1 Variable definition

3.1.1 Dependent variable

The core dependent variable in this study is the Total Factor Productivity (TFP) of the city in the given year. To achieve this, we employ multiple methods to calculate TFP, ensuring the accuracy and reliability of the results. Specifically, drawing on the methodologies of Levinsohn and Petrin (2003) and Olley and Pakes (1996), referred to hereafter as the LP method and the OP method, respectively, we primarily adopt the Data Envelopment Analysis (DEA) model. DEA is a widely used nonparametric approach for TFP measurement that evaluates production efficiency without requiring the specification of a production function, thus allowing for precise TFP estimations.

In selecting input indicators, we incorporate data from multiple dimensions. These include the baseline capital stock, reflecting the level of capital investment in the city; electricity consumption, which serves as a proxy for industrial activity and economic vitality; railway freight volume, capturing the city's logistical capacity and economic interconnectivity; and urban employment, directly linked to the city's labor resources and economic scale. Together, these input indicators form the foundation for our TFP evaluation.

For output indicators, we account for both desirable and undesirable outputs. The desirable output includes the city's GDP for the year, representing its economic output over the specific period. The undesirable outputs encompass environmental pollutants, such as sulfur dioxide, industrial wastewater discharge, and smoke emissions. The inclusion of these indicators allows for a more comprehensive assessment of the environmental impacts of urban economic activities, thereby contributing insights into sustainable development. Additionally, all monetary variables are deflated to constant 2010 prices for consistency.

In the main regression model analysis, we prioritize results derived from the LP method due to its ability to effectively control for unobservable heterogeneity in panel data. For robustness checks, we supplement our analysis with results from the OP method, which considers changes in firm productivity and adjustment costs of production factors, thereby providing more robust TFP estimates.

3.1.2 Focus variables

(1) Urban polycentric spatial structure is one of the core explanatory variables. Typically, this metric describes the degree of even distribution in the "importance" of centers within a city, where "importance" can be quantified using factors related to urban form, such as labor force population size, regional GDP, or regional transportation (Meijers and Burger, 2010; Rossi-Hansberg and Wright, 2007; Burger and Meijers, 2012). In this paper, we define the degree of urban polycentricity as a quantitative representation of the distribution characteristics of multiple central nodes in the urban spatial structure and their functional intensity, reflecting the spatial dispersion and agglomeration of factors such as economic activities, population distribution, and public service facilities within the city.

So the polycentricity measure adopted in this paper is based on the distribution of population within the city, as population distribution directly reflects the internal spatial structure of the city and serves as a foundation for the distribution of urban production and consumption activities. Following the principle of data availability, this study employs *LandScan* population distribution data to capture the average 24-hour population distribution within the city. This dataset integrates various economic activities within the region, including employment, residence, and transportation, during the estimation process and allocates the population involved in economic activities to a grid cell scale of one square kilometer. This approach allows for a direct observation of population density across different grid cells within the city when analyzing urban sub-centers. Widely used in urban economics, this data effectively captures the spatial distribution of economic activity within cities.

Using the aforementioned techniques, this article identified a number of population centers in Chinese cities between 2010 and 2019 using the Landscan database. These centers included both main and secondary centers, and the population corresponding to each center was calculated by adding up the grids in each population center. This article measures the level of urban polycentricity using the ratio of each sub-center's population ($Pop_{subcenter,it}$) to all population centers ($\mathrm{Pop}_{\mathrm{subcenter,it}}$ + $\mathrm{Pop}_{\mathrm{center,it}}$), based on the viewpoint of morphological polycentricity. The significance of the city's secondary center in relation to its main center is represented by this indicator. The larger the indicator value, the higher the proportion of the secondary center population in the city, the more important the secondary center, and the more polycentric the city. The specific calculation can be expressed by Equation 1:

$$\boldsymbol{Poly_{it} = Pop_{subcenter,it} \Big/ \left(Pop_{subcenter,it} + Pop_{center,it}\right)} \tag{1}$$

(2) City size is also the main explanatory factor in this research. Since a city's population size might fluctuate based on a number of variables, we mainly utilize the logarithm of the average permanent population of the city as a proxy variable for city size.

3.1.3 Control variables

In order to reduce estimation bias due to omitted variables, also refer to Combes et al. (2015)'s research results on urban and regional economics, we select control variables that may influence urban TFP. These control variables include the level of foreign direct investment (*FDI*), local human capital (*Hr*), research and development intensity (*R&D*), and *GDP per capita* (*Pgdp*). Specifically, foreign direct investment (*FDI*) represents the depth of capital flow and international cooperation; local human capital (*Hr*) reflects the region's educational and skill base; research and development intensity (*R&D*) measures the capacity for innovation and technological advancement; and GDP *per capita* (*Pgdp*) gauges the prosperity of the economy in terms of material wealth. By incorporating these variables, we aim to control for other factors that may affect total factor productivity, thereby enhancing the accuracy of the model's estimates. Table 1 provides the comprehensive definitions of these variables.

3.2 Empirical model

This study establishes a two-way fixed effect model (Equation 2) to investigate the relationship between polycentric structure, city size, and regional TFP:

$$\boldsymbol{TFP_{it} = \alpha_0 + \alpha_1 Poly_{it} + \alpha_2 Size_{it} + \alpha_i Control_{it} + Year_t + Prefecture_i + \varepsilon_{it}} \tag{2}$$

Among them, TFP_{it} represents the total factor productivity of the city, which is mainly calculated by the OP method and the LP method in this paper. $Poly_{it}$ represents the degree of polycentricity in the city, specifically measured by the even distribution of "importance" among the centers within the city. $Size_{it}$ represents the measurement of the city size, which includes the city population

TABLE 1 Variables definitions.

Variables type	Symbol	Definition
Dependent variable	TFP	TFP measured by the LP and OP method
Explanatory variable	Poly	Polycentric index
	Size	The logarithm of the average annual resident population
Control variables	FDI	Actual use of foreign capital for the year (US $, reduced to 2010)
	Hr	Human resources (population with tertiary education)
	R&D	Proportion of urban scientific undertakings expenditure in fiscal expenditure
	Pgdp	Gross regional product *per capita* (2010 deflated, 10k yuan)
	Area	Built-up area of the previous year (10,000 square meters)

size and built-up area in this paper. $Control_{it}$ represents the control variables of a series of sample cities introduced in Section 3.1, $Year_t$ and $Prefecture_i$ represent the time fixed effect and city fixed effect respectively, and ε_{it} represents the regression residual term.

3.2.1 Sources of bias and instrumental variable selection

(1) Endogeneity is a common issue in economic research, particularly in the field of urban economics, where it typically arises from the mutual influence and interdependence between variables. In the context of this study, a key source of endogeneity is the cause of urban polycentricity. The emergence of urban polycentricity is not only influenced by urban planning but is also profoundly constrained by natural geographic factors. In the early stages of urban development, elements such as rivers, mountains, and coastlines have already played a crucial role in the selection of urban locations, spatial layout, and subsequent urban expansion. The influence of the natural environment has, to some extent, shaped the spatial structure of cities and determined whether multiple development centers can emerge. Thus, urban polycentricity may not solely be driven by policies or human interventions; geographic factors also play a significant role. This endogenous relationship makes it difficult to eliminate the interference of external factors when analyzing the impact of polycentricity on urban Total Factor Productivity (TFP), potentially leading to biased estimation results.

To address the issue of endogeneity, a commonly used method is the Two-Stage Least Squares (2SLS) estimation. This method mitigates the bias caused by endogeneity by introducing instrumental variables to replace the endogenous variables. Instrumental variables must meet two essential requirements: first, they must be strongly correlated with the endogenous variable; second, they must be uncorrelated with the error term in the regression model, i.e., they must exhibit exogeneity. In this study, we select surface roughness (Rugg) as an instrumental variable for urban polycentricity. There are two main reasons for choosing surface roughness as an instrumental variable:

First, from the perspective of correlation, the flatness of the terrain directly influences the formation of urban spatial structure. Cities with flatter terrain are more conducive to the development of polycentric centers, as flat landscapes are better suited for large-scale urban expansion, infrastructure construction, and population concentration. In contrast, cities with more rugged terrain typically exhibit a monocentric spatial structure, as the uneven topography limits the available space for population agglomeration and urban expansion, while also increasing the costs of infrastructure construction and maintenance.

Second, from the perspective of exogeneity, although human activities may modify the terrain to some extent, such modifications are limited and the roughness of the terrain is unlikely to change significantly in the short term. Therefore, surface roughness can be considered an exogenous instrumental variable, meeting the requirements for the Two-Stage Least Squares (2SLS) method. By using this instrumental variable, we can effectively address the estimation bias caused by the endogenous relationship between urban polycentricity and natural geographic factors, thus obtaining more accurate and reliable regression results.

(2) In addition to the potential endogeneity between urban polycentricity and TFP, there may also be an endogeneity relationship between city size and TFP. Specifically, the endogeneity between city size and TFP could stem from the interaction between urban economic development and population mobility. The expansion of city size is often a result of urban economic growth, while a larger city size may also stimulate more investment and innovation, thereby further boosting TFP. On the other hand, improvements in TFP may attract more businesses and labor, leading to the expansion of city size. Therefore, the mutual influence between city size and TFP could create a bidirectional causal relationship, resulting in endogeneity issues.

To address this issue, we also apply the Two-Stage Least Squares (2SLS) method and select the built-up area of the city in the previous year (Area) as an instrumental variable for city size. There are two main reasons for choosing built-up area as the instrumental variable: First, from the perspective of correlation, the built-up area of a city is highly correlated with its population size. A larger built-up area means more space to accommodate a larger population and provide more residential, commercial, and public service areas. Therefore, the size of the built-up area is closely related to the city's population size, which in turn influences the expansion of city size.

Second, from the perspective of exogeneity, the built-up area is determined by historical urban expansion and land development patterns. While human activities may influence the expansion of the built-up area to some extent, these effects are typically lagged, and changes in built-up area are not directly affected by the current level of TFP. Therefore, the built-up area can be regarded as an exogenous instrumental variable that satisfies the exogeneity requirement for instrumental variables in the Two-Stage Least Squares (2SLS) method. In other words, although city size may be subject to feedback effects from TFP levels, the built-up area as an instrumental variable is largely unaffected by TFP, thus avoiding the interference of endogeneity on the estimation results.

(3) Model Specification for 2SLS: In the first stage, we regress the endogenous variables (such as urban polycentricity or city size) as the dependent variable, using the instrumental variables (such as surface roughness or the built-up area from the previous year) as the independent variables. We develop the following regression models for the first stage, mathematically formulated in Equations 3, 4 respectively:

$$\boldsymbol{Poly_{it} = \beta_0 + \beta_1 Rugg_{it} + \beta_i Control_{it} + Year_t + Prefecture_i + \varepsilon_{it}} \tag{3}$$

$$\boldsymbol{Size_{it} = \beta_0 + \beta_1 Area_{it-1} + \beta_i Control_{it} + Year_t + Prefecture_i + \varepsilon_{it}} \tag{4}$$

where, $Poly_{it}$ (or $Size_{it}$) represents the urban polycentricity index and city size for city i in year t, and $Rugg_{it}$ and $Area_{it-1}$ represent surface roughness and the built-up area from the previous year, respectively. The other variables are the same as in model (2). The second-stage model remains as Equation 2, but the results from the first-stage regression are incorporated into the main model.

3.2.2 Mechanism Modelling

The above theoretical explanation and analysis of the impact mechanism of multicenter and city size on urban TFP have been verified based on the results of empirical analysis. The following needs to carefully examine the mechanism by which urban spatial structure affects centralization and knowledge spillover. To examine the possible mechanisms, this paper adapts the Jiang (2022) mediation effect analysis framework, establishing the following two models mathematically formulated in Equations 5, 6 respectively:

$$\boldsymbol{M_{it} = \alpha_0 + \alpha_1 Poly_{it} + \alpha_2 Size_{it} + \alpha_i Control_{it} + Year_t + Prefecture_i + \varepsilon_{it}} \tag{5}$$

$$\boldsymbol{TFP_{it} = \theta_0 + \theta_1 M_{it} + \theta_i Control_{it} + Year_t + Prefecture_i + \varepsilon_{it}} \tag{6}$$

where, M_{it} represents the potential mechanism variable, while the remaining variables in the equation are consistent with the baseline regression.

3.3 Data source

The urban polycentric index, the study's primary explanatory variable, comes from the *LandScan* Global Population Distribution Dataset, which was created by the U.S. Department of Energy's Oak Ridge National Laboratory (ORNL). The extended time series and great resolution of this dataset are well known. We make use of the 1 km resolution of the dataset, which yields accurate urban population density estimates that represent the average population distribution over a 24-h period.

The statistics for Total Factor Productivity (TFP) and other city control variables are sourced from the China Urban Statistical Yearbook, China Urban Construction Statistical Yearbook, China Transport Statistical Yearbook, and China Energy Statistical Yearbook. The study's first research sample consists of Chinese cities at the prefecture level between 2010 and 2019. Data from the China National Geographic Conditions Monitoring Cloud Platform's Digital Elevation Model and city level terrain slope data obtained from the National Intellectual Property Administration's patent authorization and citation data are also used in this study to perform endogeneity and mechanism tests.

We use the following criteria for sample selection in order to guarantee the reliability and consistency of the results. We take into account city mergers and divisions and eliminate cities with obvious administrative boundary changes during the study period, samples with large data gaps, and the top and bottom 1% of cities in terms of sample size. Ultimately, we are left with 276 cities out of 2,710 samples.

TABLE 2 Descriptive statistics of variables (observations = 2,710).

Variable	Mean	Std. Dev	Min	Max
TFP (OP)	1.0106	0.0627	0.5713	1.763
TFP (LP)	1.0084	0.0623	0.5047	1.9979
Poly	0.0234	0.0434	0.0052	0.0836
Size	15.1377	0.6587	12.6105	17.3466
Fdi	10.0176	1.9068	1.3863	14.9413
Hr	10.4594	1.348	0.3221	13.7814
Rd	9.4896	1.7592	3.8067	15.5293
Pgdp	6.4926	1.1545	3.2813	10.5495
Area	7.0556	0.937	3.9703	9.6884

4 Empirical results and analysis

4.1 Descriptive statistics

For the variables included in this paper, descriptive statistics are provided in this section. Table 2 displays the results. The OP technique yielded an average TFP of 1.01 for the main variables, with a standard deviation of 0.063 and a range of 0.571–1.763. These values demonstrate the significant variations in production efficiency among the various cities. Regarding urban area, the mean population size of Chinese cities included in the sample is approximately 3.72 million ($\acute{e}$15.13), with notable variations in size across the various cities.

4.2 Main results

The baseline regression results of the effect of polycentricity and city size on TFP are shown in Table 3.

TABLE 3 Effect of polycentricity and city size on TFP (Total Factor Productivity).

Variables	(1)	(2)	(3)	(4)	(5)	(6)
	TFP(OP)	TFP(OP)	TFP(OP)	TFP(OP)	TFP(OP)	TFP(OP)
Poly	−0.2022***	−0.2013***	−0.2038***	−0.2032***	−0.1996***	−0.1892***
	(0.0275)	(0.0275)	(0.0274)	(0.0274)	(0.0270)	(0.0270)
Size		0.0050***		0.0058**		0.0044*
		(0.0018)		(0.0024)		(0.0023)
Observations	2,710	2,710	2,710	2,710	2,710	2,710
Controls	No	No	Yes	Yes	Yes	Yes
Year FE	No	No	No	No	Yes	Yes
City FE	No	No	No	No	Yes	Yes

Note: Standard errors in parentheses, ***p < 0.01, **p < 0.05, *p < 0.1. Columns (1–2) control for any fixed effects, columns (3–4) add city-related control variables, and columns (5–6) add year and city fixed effects.

Table 3's columns (1–2) show the regression findings for models that simply use the urban polycentricity index and models that use both polycentricity and city size, without any fixed effects or control variables. When no other factors are present, urban polycentricity significantly reduces Total Factor Productivity (TFP), as shown by column (1)'s negative and statistically significant coefficient for urban polycentricity at the 1% level. Moreover, the coefficient for city size in column (2) is positive and significant at the 1% level, indicating that city size growth positively affects town productivity.

To capture other factors that can affect TFP, we include additional city-level characteristics in the regression analysis shown in columns (3–4). The findings show that the coefficients for urban polycentricity and city size essentially stay the same even after adjusting for these extra city-specific factors. This implies that our preliminary results are solid. In particular, the coefficient for city size stays positive and the coefficient for polycentricity stays negative, thereby reaffirming the positive influence of city size on TFP and the negative impact of urban polycentricity on TFP.

We adjust for time invariant city-specific characteristics and macroeconomic effects by controlling for both city and year fixed effects in the regression analysis shown in columns (5–6). In this instance, the city size coefficient is still significantly positive, but the urban polycentricity index coefficient is still significantly negative. According to this finding, the polycentric spatial structure still significantly reduces urban TFP even after controlling for time effects and unobservable city heterogeneity, but city size growth somewhat increases TFP. There is no doubt that hypothesis 1 is confirmed. Based on data from Asian countries, Bac (2024) found based on Vietnam's experience that excessive polycentricity will have a negative impact on the economic structure. At the same time, this phenomenon is not unique to developing countries. Caset et al. (2023) also found based on data from 34 European countries that areas with high levels of urban polycentricity usually have lower productivity levels.

An intriguing finding emerges from comparing the data in columns (5) and (6): the estimated effect of polycentricity may capture the influence of city size when city size is excluded. In particular, column (6) shows a tiny decrease in the absolute value of the urban polycentricity coefficient. Although this decrease is small, it indicates that the negative effects of polycentricity are somewhat offset by the growth of the city. This could suggest that the coordination costs and efficiency losses linked to a polycentric structure are somewhat mitigated by the expansion of the metropolis, which offers more market opportunities and economic activity.

4.3 Endogenous test results

We use the Two-Stage Least Squares (2SLS) method for regression analysis, and the results are presented in Table 4.

Based on the first-stage estimation results in columns (1–2) of Table 4, we can confirm that the instrumental variables are highly correlated with urban polycentricity and city size. Specifically, the regression coefficients for the instrumental variables (such as surface roughness and built-up area) with respect to urban polycentricity and city size are in the expected direction and show statistically significant correlations with the endogenous variables. To further validate the effectiveness of the instrumental variables, we examined the F-statistics in the regression models. The results indicate that the F-statistics are all greater than 10, suggesting a strong correlation of the instrumental variables (Stock and Yogo, 2002).

In the estimation results in columns (3–5) of Table 4, the coefficients for urban polycentricity and city size are generally consistent with the baseline regression results in Table 3, but their absolute values have noticeably increased. This change indicates that after applying the 2SLS method, the effects of urban polycentricity and city size on TFP have been amplified, and the estimation results are more accurate. In contrast, the OLS regression may underestimate these effects. Specifically, in column (5), for every 1% increase in urban polycentricity, city TFP decreases by 0.24%, while for every 1% increase in city size, city TFP increases by 0.87% (where $e^{0.0087}-1 \approx 0.0087$). This result suggests that, without considering endogeneity, OLS regression may underestimate the negative effect of urban polycentricity and the positive effect of city size on TFP.

By comparing the results with the OLS regression, we further validate the effectiveness of the 2SLS method in addressing the

TABLE 4 Effect of urban polycentricity and city size on TFP: Instrumental variable regression.

Variables	(1)	(2)	(3)	(4)	(5)
	First stage		Second stage		
	Poly	Size	TFP(OP)	TFP(OP)	TFP(OP)
Poly			−0.2449***	−0.2467***	−0.2480***
			(0.0538)	(0.0537)	(0.0538)
Size				0.0050***	0.0087**
				(0.0018)	(0.0042)
Rugg	−0.3285***				
	(0.0109)				
Area		0.0015***			
		(0.0001)			
Observations	2,710	2,710	2,710	2,710	2,710
Year FE	Yes	Yes	Yes	Yes	Yes
City FE	Yes	Yes	Yes	Yes	Yes
KP F-statistic			913.6	914.1	293.7

Note: Standard errors in parentheses, ***p < 0.01, **p < 0.05, *p < 0.1. Column (4) includes only the instrumental variable for polycentricity, while column (5) includes both the instrumental variables for polycentricity and city size.

TABLE 5 Robustness test: Replace variables and lagged explanatory variable.

Variables	(1)	(2)	(3)	(4)	(5)
	Forward. TFP(OP)	TFP(LP)	TFP(OP)	TFP(OP) 2010–2014	TFP(OP) 2015–2019
Poly	−0.0739**	−0.1981***	−0.1988***	−0.2262***	−0.1740***
	(0.0305)	(0.0270)	(0.0270)	(0.0447)	(0.0314)
Size	0.0061***	0.0051***		0.0033	0.0065***
	(0.0016)	(0.0018)		(0.0029)	(0.0021)
Pop density			0.0606*		
			(0.0347)		
Observations	2,434	2,710	2,710	1,331	1,379
Year FE	Yes	Yes	Yes	Yes	Yes
City FE	Yes	Yes	Yes	Yes	Yes

Note: Standard errors in parentheses, ***p < 0.01, **p < 0.05, *p < 0.1. Column (1) considers the impact of polycentricity and city size on the lagged TFP; column (2) uses the LP, method to measure TFP; column (3) replaces city size with population density; columns (4–5) divide the sample based on time.

endogeneity issue. While the OLS regression may underestimate the effects of polycentricity and city size due to endogeneity, the use of instrumental variables in the 2SLS method provides more accurate regression estimates, supporting the hypothesis in this paper regarding the impact of urban polycentricity and size on TFP. Therefore, these results not only align with our expectations regarding endogeneity but also offer valuable insights for urban planning and development policies, particularly when considering the impact of spatial structure and city size on economic efficiency.

4.4 Robustness checks

To ensure the reliability of the results, we conducted the following three robustness tests in Table 5.

(1) Consider urban polycentricity and hysteresis in scale expansion. The improvement of regional TFP cannot be achieved in the short term, and the urban spatial structure in this article reflects the long-term variation of urban

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TABLE 6 Heterogeneity analysis: Whether it is a coastal city and the size of the city.

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Non-coastal city	Coastal city	Population size			Population density	
			< 2 million	2~5 million	>5 million	> 500/km^2	< 500/km^2
Poly	−0.1263***	−0.1976**	−0.2338***	−0.1405***	−0.0828***	−0.1933***	−0.0443
	(0.0280)	(0.0793)	(0.0797)	(0.0379)	(0.0046)	(0.0324)	(0.0380)
Size	0.0021	0.0052***	−0.0040	−0.0031	0.0128**	0.0012	0.0053*
	(0.0019)	(0.0016)	(0.0091)	(0.0072)	(0.0060)	(0.0025)	(0.0030)
Observations	2,190	520	450	1,243	1,011	1,671	1,039
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
City FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Note: Standard errors in parentheses, ***p < 0.01, **p < 0.05, *p < 0.1. Columns (1–2) use whether the city is located on the coast as the classification standard, columns (3–5) use population size as the classification standard, and columns (6–7) use population density as the classification standard.

development. By replacing the explanatory variables with the second year, there is no significant difference in the estimation results.

(2) Considering the robustness of the explained variable and the explanatory variable, in column (2) we use the TFP calculated by the LP method instead of the TFP calculated by the OP method as the dependent variable, and in column (3) we use population density instead of population size as the independent variable, respectively, to eliminate the risk of indicator measurement bias.

(3) Finally, due to China's hukou system reform in 2014, which allowed a large number of people to obtain urban residency, we test the samples before and after 2014, yielding the results in columns (4–5). Overall, regardless of the method used, urban polycentricity has a negative impact on TFP, while the expansion of city size has a positive impact on regional TFP. Moreover, these effects are both significant and robust.

4.5 Heterogeneous effects

To explore the heterogeneity of urban location and size, this study conducts the following estimations, with results presented in Table 6. As shown in columns (1–2) of Table 6, we divide the sample data into non-coastal and coastal cities. It is evident that the negative impact of polycentricity on regional TFP is more significant in coastal cities, and the positive impact of city size expansion on TFP is only significant in the coastal city sample. columns (3–5) examine the heterogeneity among small and medium-sized cities, large cities, and super-large cities. The results show that the negative impact of polycentricity gradually weakens, while the positive impact of city size expansion follows the opposite trend, being significantly evident only in super-large cities with populations over 5 million. In this regard, based on the estimation results from columns (2) and (5), we hypothesize that this may be related to the specific industrial and population distribution in China. Most large cities and industries are located in the southeastern coastal areas of China, which also have more mountainous regions. Consequently, polycentric distribution is common in many cities, and the expansion of city size significantly enhances TFP in these regions.

Columns (6–7) examine the heterogeneity of cities with high and low population density using 500 people/km^2 as the limit. The results show that in high-density cities, the negative impact of urban polycentricity on TFP is statistically significant, and the absolute value of its coefficient is greater than the baseline regression result. In contrast, in low-density cities, the impact of urban polycentricity on TFP is not significant. Kwon and Seo (2018) found similar results based on urbanization data in South Korea, namely, that in high-density population areas, urban polycentricity is highly negatively correlated with labor productivity.

We further explored the optimal city size. City size expansion and TFP have been shown to positively and significantly correlate, but this does not imply that cities can grow indefinitely (Scott and Storper, 2015; Su et al., 2024). Figure 1 illustrates the outcomes of fitting the city size quadratic term to TFP. Our findings indicate that TFP will sharply decline above a certain city size threshold, indicating that urban development must balance size expansion with economic benefits. Hypothesis 2 is supported by the data.

Therefore, we further add the quadratic term of city size into model (1). The regression results are shown in Table 7, where we verify whether control variables are included and examine the optimal city size for coastal and inland cities. Without considering city related control variables, the optimal city size is approximately 2.36 million people. After incorporating control variables such as infrastructure pressure, environmental issues, and social services, this size decreases somewhat.

4.6 Mediating analysis

(1) Does urban polycentricity lead to an increase in the distance between centers?

Urban polycentricity may lead to an increase in the geographic distance between centers because a polycentric structure typically implies a dispersed layout of different functions and economic

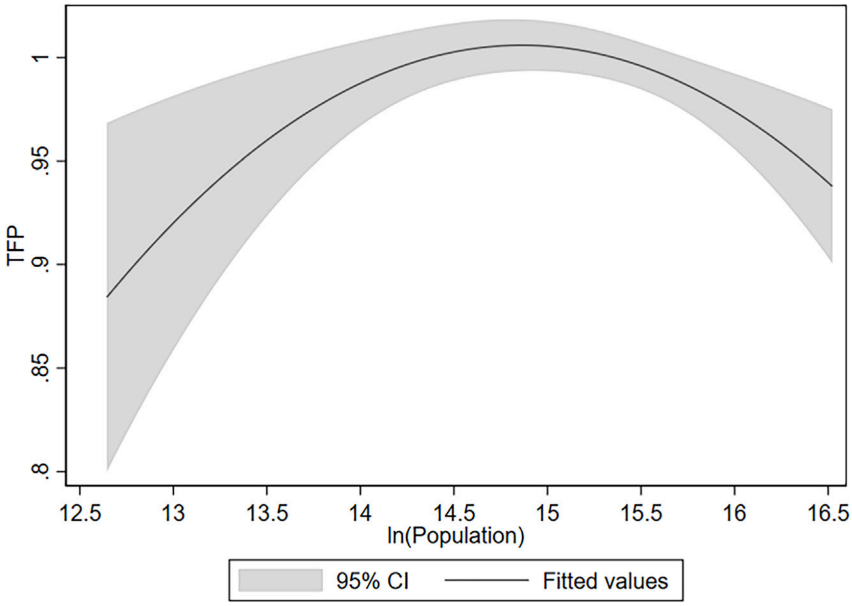

FIGURE 1
Quadratic fitting relationship between city size and TFP. (Optimal size threshold: 2.36 million people).

TABLE 7 Effect of the quadratic term of city size on total factor productivity.

Variables	(1)	(2)
	TFP(OP)	TFP(OP)
$(\text{Size})^2$	−0.0043**	−0.0035*
	(0.0020)	(0.0021)
Size	0.1262**	0.1019*
	(0.0596)	(0.0618)
Optimal City Size (Million)	2.36 M	2.10 M
Observations	2,710	2,710
Controls	No	Yes
Year FE	Yes	Yes
City FE	Yes	Yes

Note: Optimal City size = EXP (-(Coefficient of Size)/(2*Coefficient of $(\text{Size})^2$)). Standard errors in parentheses, ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$.

activities, rather than a highly concentrated single-center model. In such a structure, the various centers within the city tend to be spatially separated, thereby increasing the physical distance between them. As the process of poly-centric development advances, the dispersion between centers intensifies, and the city's spatial layout becomes more complex and fragmented, further expanding the geographic distance between centers. To explore the impact of polycentricity on the internal spatial distribution of the city, we calculate the average distance between the sub-centers and the main center's centroid in terms of latitude and longitude (Central), using this as the dependent variable in model (5), and analyze whether polycentricity increases the geographic distance between centers.

Based on the regression results in columns (1–2) of Table 8, it is clear that the regression coefficient for urban polycentricity is significantly positive, indicating that the current polycentric development model in Chinese cities indeed exacerbates the expansion of distance between centers (i.e., the average distance between centers in-creases). The decentralization of centers not only leads to a more dispersed urban spatial layout but also significantly reduces the efficiency of collaboration and resource sharing as the distance between centers increases. This change in spatial distribution may hinder interaction between businesses, thus negatively impacting the city's TFP. Therefore, while urban polycentricity can facilitate spatial expansion, it may also reduce

TABLE 8 Effect of polycentricity and city size on TFP: Mediating affects.

Variables	(1)	(2)	(3)	(4)	(5)	(6)
	Central	TFP(OP)	Patents	TFP(OP)	Citations	TFP(OP)
Poly	0.6741***		−0.3557**		−0.8365***	
	(0.1599)		(0.1657)		(0.1710)	
Size	0.3479***		0.3393***		0.3863***	
	(0.0105)		(0.0109)		(0.0112)	
Central		−0.0048*				
		(0.0028)				
Patents				0.0050*		
				(0.0027)		
Citations						0.0084***
						(0.0026)
Observations	2,710	2,710	2,710	2,710	2,710	2,710
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
City FE	Yes	Yes	Yes	Yes	Yes	Yes

Note: Standard errors in parentheses, ***p < 0.01, **p < 0.05, *p < 0.1.

the city's productivity by increasing the geographic distance between centers.

(2) Does urban polycentricity suppress urban innovation performance?

Polycentricity may suppress urban innovation activities because a polycentric structure often leads to the decentralization of innovation efforts (Liu et al., 2023). When a city develops multiple independent economic and functional centers, innovation resources and activities tend to be scattered across these centers, reducing the concentration and collaboration opportunities for innovation. This spatial dispersion increases the cost of communication and cooperation between businesses and research institutions, thereby hindering the efficiency and effectiveness of innovation activities. Aritenang (2021), based on data from technology companies in Malaysia, also agreed that technological advancement is further driving economic agglomeration, and found that more spatially dispersed industries are conducive to the long-term development of technology companies.

To test this hypothesis, we selected the number of patents granted in the city as a mediator variable to measure innovation performance (Patents). The number of patents is an important indicator of innovation activities and reflects a region's capability in technological research and innovation. The results in columns (3–4) of Table 8 confirm our expectation: urban polycentricity indeed suppresses innovation performance by reducing the total number of patents granted. A decrease in the number of patents directly implies a decline in innovation output, and innovation is a key driver of regional TFP growth. Therefore, the polycentric structure of cities may suppress overall innovation capabilities by dispersing innovation activities, thereby negatively affecting the city's TFP growth.

(3) Does polycentricity suppress innovation spillover effects?

The urban polycentric structure may suppress innovation spillover effects because the technological and knowledge spillover effects often depend on close cooperation and frequent interaction between urban centers, which can be reflected in patent citations (Citations). Polycentricity typically means that innovation activities and technological collaborations within a city are spread across different centers, weakening technological exchange and knowledge sharing between centers. As the physical distance between urban centers increases, the flow of technology and knowledge is restricted, and the innovation spillover effect may therefore be suppressed. Existing studies show that the innovation spillover effect in urban clusters largely depends on the cooperation networks and knowledge transfer between cities, and the decentralization of such networks undoubtedly weakens their effectiveness. Based on data from Japan's manufacturing industry, Otsuka (2024) also found that enhancing regional network connections and improving high-quality transportation infrastructure can offset the negative externalities caused by urban polycentricity.

According to the estimation results in column (5) of Table 8, the urban polycentric structure indeed leads to a decrease in the total number of patent citations, indicating a significant suppression of innovation spillover effects between cities. Patent citations are an important indicator of innovation spillover, as the citations between patents often reflect the dissemination and diffusion of technology and knowledge. Further analysis of the regression results in column (6) of Table 8 shows a significant positive correlation between patent citations and regional TFP, indicating that an increase in patent citations effectively promotes TFP growth. Therefore, the urban polycentric structure, by reducing patent citations, suppresses innovation spillovers, thereby negatively impacting the city's TFP growth. Obviously, the results of the mechanism test effectively prove that with the increase of the spillover effect of innovation and the multi-center distance of cities, it is possible to further lead to TFP loss, and hypothesis 3 is proved. Based on observations of the Barcelona metropolitan area, Masip Tresserra (2012) found that urban sub-centers have a positive impact on labor productivity and can alleviate the problem that the higher the expansion of the central urban area, the lower the labor productivity.

The inhibiting effect of polycentricity on innovation spillovers is clearly demonstrated in the case of the Barcelona metropolitan area. Research indicates that as urban spatial structures transition to polycentricity, the increased geographical distance and the dispersion of innovation resources significantly weaken the efficiency of cooperation between firms. This is reflected in the slowdown in patent application growth and the reduction in collaborative innovation projects between firms (Liu et al., 2023). This phenomenon is consistent with existing literature, which suggests that while polycentricity can alleviate the resource pressure on city centers, it may also lead to the fragmentation of innovation activities, thereby hindering the efficient flow of knowledge and technology (Derudder et al., 2021; Li and Du, 2022). Furthermore, Aritenang (2021), based on a study of technology firms in Malaysia, points out that spatially dispersed industrial layouts, while beneficial for the long-term development of firms, significantly increase the cost of innovation cooperation and weaken innovation spillovers within the region. Therefore, urban planning needs to enhance transportation links between centers and optimize the allocation of innovation resources in order to maintain the vitality of the innovation ecosystem and mitigate the negative impacts of polycentricity on innovation spillovers (Otsuka, 2024).

5 Conclusion and policy implications

5.1 Conclusion

In the current urbanization process, the impact of urban polycentricity and size expansion on regional total factor productivity is an important research topic, but its impact size and optimal city size have not yet been deeply explored. Based on this thinking, this paper takes urban spatial structure and scale as the main research perspective to examine the impact and mechanism of urban spatial structure on regional TFP. Specifically, based on the panel data of China's prefecture-level and above cities from 2010 to 2019, this article empirically analyzes the causal effects of urban poly-centers and size expansion on regional total factor productivity, and estimates the optimal city size for development.

The research results show that: first, urban polycentric spatial structure has a negative impact on regional TFP, and a series of robustness tests such as considering TFP time lag, replacing explained variables and explanatory variables, and exogenous household registration policy all support this A conclusion. The expansion of urban size has a significant positive impact on regional TFP. For every 1% increase in urban population, the marginal increase in total factor productivity is approximately 0.87%. This effect partly offsets the negative effect of polycentricity.

Second, in China, when many cities are developing into polycentric patterns, they will enlarge the geographical distance between urban centers and increase the geographical barriers between tacit knowledge flows. And as the distance between centers further expands, in fact, new special economic zones or scientific research centers in Chinese cities are often far away from old cities. The scale effect of each urban center will be eliminated, the center agglomeration trend will be destroyed, knowledge innovation within the city will be hindered, and multi-center It mainly suppresses urban TFP by destroying the externalities of innovation spillover within the city.

Third, from the perspective of location and city size, the polycentric spatial structure has a stronger inhibitory effect on TFP in coastal cities than inland cities. However, coastal cities can offset this negative impact within certain limits by expanding the city size and attracting population. Under the current productivity level, China's optimal city size is between 2.49 million and 2.84 million people. Excessively large city size may cause significant efficiency losses.

5.2 Policy implications

Our findings are of great reference value to governments in developing countries in terms of urban development planning policies. From a practical perspective, developing countries should avoid blindly pursuing polycentric development in urban planning, especially in areas with small cities or weak economic foundations. Although polycentric development can help alleviate traffic congestion and excessive resource concentration in monocentric cities, excessive dispersion may lead to reduced economic efficiency. It is recommended to reasonably balance the relationship between polycentric development and urban expansion according to the stage of urban development and population size. For cities with high population density, priority should be given to improving economic efficiency through moderate agglomeration rather than excessive dispersion of urban functions. At the same time, attention should be paid to offsetting the possible negative effects of polycentric development through the positive effects brought about by urban expansion (such as population growth and resource concentration). For example, economies of scale can be formed by guiding population and industry to concentrate in the core areas of cities, while secondary centers can be moderately developed in peripheral areas to achieve functional complementarity.

Given the heterogeneity analysis results, policymakers should tailor urban development strategies to specific city characteristics. For coastal cities, where polycentricity significantly hinders TFP, enhancing connectivity between urban centers through infrastructure investment is crucial. Meanwhile, coastal cities can leverage their economic advantages by moderately expanding city size to attract talent and boost innovation. For inland cities, where the negative impact of polycentricity is less severe, controlling city size and promoting moderate agglomeration should be prioritized to improve economic efficiency. Additionally, for cities with high population density, where polycentricity has a more pronounced negative effect on TFP, enhancing inter-center connectivity and optimizing urban spatial layout are essential. In contrast, for low-density cities, the focus should be on developing secondary centers to complement the core areas and improve overall productivity.

Second, strengthen the connectivity between urban centers to promote knowledge flow and innovation. In the process of polycentric development, the expansion of geographical distance between urban centers may hinder knowledge flow and innovation spillover, which is particularly prominent in developing countries. The spread of tacit knowledge often relies on face-to-face communication and high-frequency interaction, while the expansion of geographical distance may weaken such interaction. It is recommended to reduce the negative impact of geographical barriers on economic activities by investing in transportation infrastructure (such as bus rapid transit systems, rail transit) and digital platform construction. For example, the rapid flow of people, information and resources can be promoted by building an efficient inter-city commuting network and smart city platform. At the same time, promote the functional complementarity and coordinated development between new and old urban areas to avoid weakening the overall innovation ability and economic vitality of the city due to excessive dispersion. This experience is of great reference significance for developing countries to optimize the internal spatial layout of cities, especially in the process of rapid urbanization, how to improve innovation ability and economic competitiveness through spatial planning is a common challenge.

Third, optimize the scale and functional layout of cities. Developing countries should formulate differentiated urban development strategies based on their own location conditions and development stages. For coastal or economically developed cities, while promoting multi-centerization, they should focus on improving economic efficiency by moderately expanding the scale of cities and attracting high-quality population. For inland or economically underdeveloped cities, they should give priority to controlling the scale of cities to avoid waste of resources and loss of efficiency caused by excessive expansion. In addition, countries should explore the optimal city size range that suits their national conditions to avoid efficiency losses caused by cities that are too large or too small. This experience has universal reference value for the global urbanization process.

5.3 Research limitations and prospects

This paper analyzes the relationship between urban polycentralization trend and urban size expansion and TFP in China, and gives corresponding countermeasures and suggestions according to the changes of sample cities' TFP. However, due to limitations such as time constraints and data availability, the paper exhibits certain limitations that could be addressed in future studies. First of all, this paper focuses on the annual average urban centralization level, and the impact of the dynamic flow of people on TFP cannot be observed. Future research should aim at systematically and comprehensively analyzing the changes of total factor productivity through more frequent data (such as quarterly or even monthly data). Second, the paper does not delve into the analysis of TFP changes, a limitation that provides an avenue for future research to explore the topic in greater depth and nuance, that is, to further decompose TFP for technological progress or efficiency optimization. Finally, the focus of this paper on the mechanism of TFP change focuses on agglomeration effect and innovation spillover, and subsequent research may involve the construction of corresponding causal inference models to accurately examine the influence of each factor on TFP change. This method will help to provide more targeted countermeasures and suggestions for promoting the development of urban economy.

Data availability statement

The Landscan Global Population dataset is available here: https://www.eastview.com/resources/e-collections/landscan/. Prefecture-level data are sourced from the China Urban Statistical Yearbook, China Urban Construction Statistical Yearbook, China Transport Statistical Yearbook, and China Energy Statistical Yearbook. Available at: https://data.cnki.net/and https://www.stats.gov.cn/sj/ndsj/.

Author contributions

XJ: Conceptualization, Formal Analysis, Funding acquisition, Project administration, Supervision, Writing–original draft, Writing–review and editing. SW: Formal Analysis, Investigation, Methodology, Writing–original draft, Writing–review and editing. CY: Data curation, Software, Visualization, Writing–original draft, Writing–review and editing. SL: Writing–original draft, Writing–review and editing. BY: Validation, Writing–original draft, Writing–review and editing. YW: Resources, Writing–original draft, Writing–review and editing.

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Conflict of interest

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

Generative AI statement

The author(s) declare that no Generative AI was used in the creation of this manuscript.

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