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Whither less is more? Understanding the contextual and configurational conditions of polycentricity to improve urban agglomeration efficiency

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ABSTRACT

Polycentricity is at the core of the urban policy and planning debate on both city size and spatial configuration, but there is no conclusive evidence for how and when polycentricity can improve urban agglomeration efficiency. This study examines the impacts of polycentricity, as well as features of its spatial configurational, on urban agglomeration efficiency. An improved relative threshold method based on local isolines (IRT-LI) is developed to identify urban centers and sub-centers, and this indicator is regressed against agglomeration economic efficiency acquired through an input-output method—super-slack-based measure (Super-SBM). Taking 252 prefectural-level cities in China as examples, this study finds that polycentricity does not demonstrate any linear or U-Shape impact on the agglomeration economy efficiency of all cities, while the impacts become positive only when urban population and central city density surpass certain thresholds (population over 6 million and density over 6000 people/km2). Compactness in density and balance in the size of multiple centers are key spatial configurational features to improve economic efficiency, while the number of centers should only be increased for large size and high-density cities. Policymakers and planners are encouraged to limit polycentric planning only to megacities/mega-city-regions and combine compact, multi-functional, mixed land-use spatial configurations with polycentricity.

1. Introduction

The discussions of the relationship between urban spatial structure and economic efficiency have become increasingly intricate as both practical and theoretical models of urban structure have evolved beyond the traditional concept of a central business district (CBD) surrounded by residential areas (Lucas & Rossi-Hansberg, 2002), and further away from a generalized and stark dichotomy of city and suburbs (Hewings & Parr, 2007). Compact (or concentrated) urban development around one center (or CBD) was described as the most efficient spatial structure as the concentration of much of the economy's production activity would place producers, markets, and labor in proximity within cities thus promoting production externalities, as well as reducing the cost of land and ecological resources, and thus generating agglomeration economic efficiency (Lucas & Rossi-Hansberg, 2002; Yao et al., 2022). This notion is challenged by the potential agglomeration diseconomies (or "urban challenges," including congestion, pollution, and housing shortage) associated with mega-cities that have been emerging all around the world (Yao et al., 2022). The urban structure of networked (or connected) cities (or city-centers) has gained attention for their potential economic efficiency benefits, drawing strength from the functional division of labor and improved connectivity through motorways, high-speed railways, and telecommunication means (Yu et al., 2019).

Taking these factors into account, particularly in the context of mega-cities and mega-city regions, public policy and urban planning have made efforts to foster polycentric urban development. The aim is to decentralize the population, enhance the standard of living, and improve environmental quality, as well as reduce commuting time (Hu et al., 2018; Yang, Jin, et al., 2019). City-region policy worldwide, such as the UN's New Urban Agenda, European Spatial Development Perspective, IUSA metropolitan areas, Italian NUTS-2, Barcelona's metropolitan area in Spain, Turkish NUTS-5, Randstad in the Netherlands, and Rhine-Ruhr in Germany, city agglomerations in China, Korean FUR have adopted polycentric urban development, which is

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defined by proximate but distinct urban centers that function as a whole (Li & Liu, 2018).

Polycentricity is at the core of the policy and planning debate on city size and spatial configuration and attempts to explore where negative and positive externalities are balanced (Alonso, 1971). The potential of polycentricity in promoting greater efficiency within urban systems is explored through concepts such as "complementarity," "borrowed size," or "city networks." These notions highlight the benefits of polycentric development, which include leveraging the positive externalities of large megacities while avoiding the negative effects of agglomeration diseconomies (Meijers & Burger, 2017). Spatial planners focus more on the negative consequences of urban growth and in general advocate polycentric urban development models, while economists, with a primary focus on economic growth, recommend fostering large megacities through policies such as lifting growth-restricting planning regulations (Boussauw et al., 2018; Glaeser et al., 2016). Therefore, given that there has only been limited analytical evaluation of the contribution of polycentricity to maximize agglomeration efficiency, this study investigates the optimum conditions between agglomeration and polycentricity, by measuring the nonlinear relationship between city heterogeneity of polycentricity's impact on urban agglomeration efficiency.

A central issue inherent in any examination of urban polycentricity revolves around defining and measuring the concept of polycentricity itself. Identification of polycentricity is intuitive but at the same time methodologically vague. In most urbanization processes worldwide, the differences between cities and suburbs gradually blur, complicating the demarcation of urban sub-centers, and eventually polycentricity (Boussauw et al., 2018). There are many ways in which 'multiple,' '(sub) centers,' 'proximate,' and 'balanced,' can be understood and operationalized (Derudder et al., 2022). This study seeks to analyze polycentricity by considering both the number of centers and the spatial distribution characteristics, aiming to identify a spatial configuration that enhances urban agglomeration efficiency. On one hand, it refines and extends polycentricity measurements using high-resolution, gridded, intra-city population satellite data developed by Liu et al. (2018), Li and Derudder (2022), and Yang et al. (2023). In addition, this paper also explores the spatial configuration extracted from population distribution data. On the other hand, the study delves into the impacts of polycentricity, spatial configuration, and contextual conditions on agglomeration economic efficiencies, contributing to the existing body of evidence regarding the effects of polycentricity on air quality, carbon emissions, and the economic growth of cities (Han et al., 2020; Shi et al., 2023; Yang et al., 2023).

To understand when and how negative and positive externalities are balanced concerning urban polycentricity, and whether empirically the optimum has been reached in real-world cities, this paper proposes to explore three research questions: 1) what are the conditions that contribute to the effective improvement of agglomeration efficiency through polycentricity for real-world cities? 3) what types of cities have benefited from being polycentric? and 2) how to spatially configure polycentricity to improve agglomeration efficiency. How should polycentricity be spatially configured to improve agglomeration efficiency? To address these questions, this study explores 252 prefectural level and above cities in China from 2010 to 2018 as empirical examples and measures the agglomeration efficiency of each city following the method the method proposed by Yao et al. (2022), as well as their polycentricity using population density data. The relationship between urban polycentricity and agglomeration economies, as well as the functional form and thresholding of such relationship, can provide an answer to the first research question. Furthermore, dissecting polycentricity by the number of centers and distributional characteristics can help answer the second research question. Finally, understanding the heterogeneity of cities' agglomeration efficiency impacts from polycentricity can answer the third research question.

The paper is structured as follows. The next section provides a theoretical development with a literature review on urban polycentricity and agglomeration efficiency and then puts forward the hypotheses of the paper. The third section presents the data and methodology while the fourth section introduces the empirical results. Section 5 discusses the results along with their policy implications, and the final section concludes the paper.

2. Theoretical development

2.1. Effects of polycentricity on the efficiency of urban agglomeration economies

Polycentricity emerges in an attempt to diminish agglomeration diseconomies compared to the overcrowded CBD thus improving the efficiency of agglomeration economies inside city-regions (Anas et al., 1998). Urban agglomeration diseconomies, such as traffic congestion, pollution, housing shortage, and urban heat island (Wang et al., 2019; Zhang et al., 2017), are supposed to be mitigated by polycentric development. Han et al. (2022) find that polycentric structures can reduce the surface urban heat island intensity at the city-proper level in China by dispersing industrial plants away from urban centers while centralizing green spaces. However, some scholars do not always support these theoretical conjectures and argue that urban polycentricity is merely a placebo or, in some cases, even a pathogen. Li and Du (2022) reveal a significant and negative causal relationship between polycentricity and cities' innovation capacity in China. Wang et al. (2019) show that intra-urban monocentricity is linked with higher levels of labor productivity than polycentricity in China. The current evidence does not support a conclusive argument for the benefits of urban polycentricity on agglomeration economic efficiency, while most evidence confirms the positive effects on environmental outcomes of polycentricity (Li et al., 2022). A recent review of empirical studies on polycentric spatial structures cautions planners and policymakers against a sweeping promotion of polycentric development since its effectiveness depends on a number of factors, including weak theoretical positioning, ambiguous conceptualization, context dependence (Dadashpoor et al., 2023).

At the same time, they may also be a complementary benefit to urban efficiency by "borrowing size" among urban (sub)centers, making the sum of sub-centers more than its constituent parts (Li & Liu, 2018; Meijers & Burger, 2017). The emergence of information and communication technologies facilitates the interactions between sub-centers in a city. The synergies arising from the interaction can produce agglomeration economies that are observed in a single urban core of a roughly similar size, enabling the "borrowing" of urban sub-centers (Wang et al., 2019). Zhang et al. (2017) found that, in China, the availability of the Internet has been found to serve as a mediator to enhance the effects of polycentricity on urban labor productivity. Wang et al. (2022) find that polycentricity boosts the positive functional spillovers of the producer service sector and labor productivity beyond city boundaries only for large cities with strong infrastructure connectivity. Thus, the "borrowing size" benefits of urban polycentricity depend on the advancement of information and transportation technologies as well as purely urban size.

Moreover, cities of various sizes and characteristics show differing benefits from polycentric structures. Han et al. (2020) examine the effects of polycentricity on air pollutants (PM2.5) for cities in China and find that pollutant concentrations are lower in low-density cities with a strong-monocentric spatial structure and in high-density cities with a polycentric structure. Shi et al. (2023) find that a monocentric structure is more conducive to reducing carbon emissions for cities with less than about 1 million population while a polycentric structure is more conducive for larger cities. Yang et al. (2023) reveal that the impact of urban polycentricity on economic growth is nuanced, influenced by factors such as population size and inter-city interactions. Therefore, when planning for polycentricity, it is crucial to consider and evaluate multiple factors, including the characteristics of cities, the extent of polycentricity, and the trade-offs among various goals of agglomeration economies.

2.2. Measurement of urban polycentricity

Studies of polycentricity identify two dimensions of polycentricity: form (morphology) and function (Li et al., 2022). Population and night-light satellite images are useful to represent form polycentricity. Liu and Wang (2016) examine the spatial structure of the urbanized areas within individual cities and identify polycentricity of Chinese cities using detailed gridded population data. Lv et al. (2021) analyze polycentricity of Chinese cities using geospatial big data including points of interest (POIs), road networks constituted street blocks, and social media check-in data. Among various types of data, population density grids and land use data are frequently utilized in studies related to polycentricity. Some studies also supplement existing datasets with other sources of big data to enhance their analyses.

Representation of function polycentricity is more varied, using employment, firm type, and other types of data. For example, Li and Phelps (2018) measure the functional polycentricity of China's Yangtze River Delta Region using data on co-publications as an indicator of knowledge linkages. Data such as commuting can be used to imply both form and function polycentricity. However, compared to form (morphology) polycentricity, function polycentricity is not yet as well-defined, and may not be as prominent. It is found that morphology polycentricity is more often identified than function polycentricity when comparing the differences between size, connectivity, and self-sufficiency (Burger & Meijers, 2012). For instance, a study conducted in Shanghai revealed that the functional sub-centers identified using mobile phone communication data do not always align with, and typically lag, the morphological polycentricity recognized through land development patterns (Yue et al., 2019).

As for the methods employed, most studies adopted spatial clustering on population centers in determining polycentricity of cities (Yu et al., 2022), with other methods ranging from administrative definitions to standard deviation-based methods, entropy-based or composite indices (Sun & Lv, 2020), rank-size regression approaches (Li & Du, 2022), network and/or centrality-based methods, and benchmarking/thresholding methods comparing observed polycentricity to optimized agglomeration efficiency (Pan et al., 2018). Vasanen (2012) presents a new approach to measure functional polycentricity by examining the connectivity of individual centers to the whole urban system. Taubenböck et al. (2017) analyze conceptually different kinds of threshold approaches to the concept of polycentricity with a combination of 3D building structures and remote sensing data. Meijers and Burger (2010) and Ouwehand et al. (2022) have pioneered the development of morphological measurements for multidimensional polycentricity with an examination of urban population presence and distribution over a region. Yang, Pan, et al. (2019) employed a spatial equilibrium model to measure polycentricity in Shanghai. They utilized a wide range of datasets, including official statistical data, land market transactions, and proprietary digital data from online sources, to construct their analysis.

While Yang, Pan, et al. (2019) method offers valuable insights into city-level polycentricity, its significant data requirements pose challenges for widespread applicability. Therefore, there is a pressing need to reconcile the comprehensive approach of Yang, Jin, et al. (2019) with the more feasible methodologies of Meijers and Burger (2010), and Ouwehand et al. (2022). Liu et al. (2018), Li and Derudder (2022), and Yang et al. (2023) strike a balance between the two approaches by developing methods that can effectively measure city-level polycentricity with satellite imagery and gridded population data. However, to guide spatial planning, measuring just "how polycentric" is not adequate, and gridded population data should be further developed to understand spatial configuration characteristics of polycentricity, such as a nuanced understanding of intra-city population distribution and presenting a holistic view of how polycentricity can be optimized for the most efficient conditions of agglomeration.

2.3. Theoretical questions and hypotheses

In this section, we will develop a set of questions and propose hypotheses based on the findings, interpretations, and insights derived from the existing literature. In this paper, polycentricity is defined by composite indicators including "large numbers of centers, balanced size among different centers, and compact central city." The main research questions of this study are as follows:

1) what are the conditions that contribute to the effective improvement of agglomeration efficiency through polycentricity for real-world cities?
2) what types of cities would benefit more from being polycentric?
3) how should polycentricity be spatially configured to improve agglomeration efficiency?

Polycentricity does not always guarantee urban agglomeration economy efficiency under all circumstances. There are two main reasons: 1) agglomeration economies occur in a single city center when the center is not large enough to induce any diseconomies; 2) connection barriers among too many centers can compromise economic efficiency. Many studies have proposed non-linear or thresholding relationships for urban form and economic efficiency. U-shape curve and population (density) thresholds have been used for such characterization (Ma et al., 2022). While both non-linearity and threshold relate to the first research question on the relationship between polycentricity and agglomeration efficiency, only the functional relationship will be examined by the first hypothesis since threshold also relates to the second research question and will be examined later. Thus, the first set of hypotheses is as follows:

H1a. The relationship between polycentricity (large numbers of centers, balanced size among different centers, and compact central city) and urban agglomeration efficiency follows a U-shape curve.

H1b. There is a positive relationship between polycentricity and urban agglomeration efficiency.

Polycentricity is often advocated as a strategy to alleviate agglomeration diseconomies that may arise when cities reach a certain size. The concept of a threshold is used to capture the relationship between polycentricity and urban agglomeration efficiency. Population and population density are the two most often used thresholds to characterize the relationship between urban form and efficiency (Ding et al., 2022). These thresholds are also highly relevant to the second research question regarding city type and polycentricity: larger cities with overcrowded centers tend to have benefited from polycentricity to reduce agglomeration diseconomies. Thus, the second set of hypotheses of this study comprises:

H2a. Agglomeration economy efficiency of larger-scale cities benefits more from polycentricity.

H2b. Agglomeration economy efficiency of cities with more crowded centers benefits more from polycentricity.

For polycentricity, its impact on economic efficiency is closely linked with its measurement. Indicators such as the number of centers, compactness, and hierarchy of sizes of the centers have been used to measure polycentricity as well as characterize polycentric spatial configurations (Li et al., 2019). The relationship between different measurements of spatial configurations in the context of polycentricity has been relatively understudied, leading to a lack of evidence in this area. This knowledge gap gives rise to the third research question of this study. Thus, the third set of hypotheses is:

H3a. When sub-centers demonstrate a more distinct hierarchy of size, polycentricity shows stronger positive effects on agglomeration economy efficiency.

H3b. When sub-centers are more compact, polycentricity shows stronger positive effects on agglomeration economy efficiency.

Finally, the answers to the optimal spatial configuration (question 3) link to the answers to the city-type heterogeneity (question 2). When city size becomes larger and density becomes higher, larger numbers of sub-centers would be necessary and justified. Thus, our final set of hypotheses are:

H4a. Agglomeration economy efficiency of larger-scale cities benefits more from larger numbers of city centers (a specific spatial configuration measure of polycentricity).

H4b. Agglomeration economy efficiency of cities with more densely populated central cities benefits more from a larger number of city centers.

3. Materials and methods

3.1. Identification of urban centers from spatial population grids

Threshold-based methods have been widely used for urban boundary delineation and core-periphery identification (Arribas-Bel et al., 2021; Moreno-Monroy et al., 2021). This paper develops an improved relative threshold method based on local isolines (IRT-LI) to identify urban centers and sub-centers. Traditional threshold-based methods for identifying major urban centers often focus on densely populated areas, which may not fully capture the polycentric nature of urban regions that extend beyond a single center. The major advantage of the IRT-LI method is that it can identify multiple peaking densities within an urban boundary, that can be revealed as urban sub-centers.

The main idea is to draw multiple isolines for the population grid of a city, with a quantile threshold of the population grid used for the first isoline, and then stepwise population decrease thresholds used for the remaining isolines. The first isoline delineates the city center, and all contiguous areas within the remaining isolines are identified as sub-centers. Based on previous calibration of China's urban boundary detection (Chen et al., 2017), the 95 % quantile and 3000 population stepwise decrease with each isoline is used. Other parameter settings also follow established studies (Chen et al., 2017; Liu & Wang, 2016). Assuming that the non-zero population grid of a city is sorted in decreasing order, the 95 % quantile has a population q, and the population of a grid i is p_i, specific steps are as follows (Fig. 1):

Step 1: Screen out the grids that meet the following conditions: 1) $p_i \geq q$; 2) at least 3 grids are connected; 3) the total population of the connected grid exceeds 50,000. Suppose that the grids identified at this stage form N contiguous regions. These regions can be considered as candidates for the first-tier regions.
Step 2: Within each of the N continuous regions, screen out grids that meet the following conditions: 1) $p_i \geq q + 3,000$; 2) at least three grids are connected. Assuming that such grids do not exist within the M regions among N ($M \leq N$), then the M regions are defined as a first-tier region; within the remaining N-M regions that have such continuous grids, assuming that K regions are formed within N-M ($K \geq N$-M), proceed to next step with the K regions as additional first-tier region candidates.
Step 3: Reiterate step 2 to further screen out continuous areas until the termination condition $p_i \geq q + 9,000$ with interval steps of 3000 population increase is met, and define the L regions meeting the termination conditions, as well as the L' regions do not meet the conditions in any previous steps ($L' \leq K$ and $L \geq K$-L') as first-tier regions.

3.2. Measurement of polycentricity and spatial configuration

The polycentricity, and spatial configuration measurements (hierarchy of size, compactness, numbers of centers) are key to answering all of our research questions. After identifying the urban centers, we can directly determine N as the total number of urban centers, including both main centers and sub-centers. Additionally, other measurements can be calculated as follows:

$$poly = N*var*compact \tag{1}$$

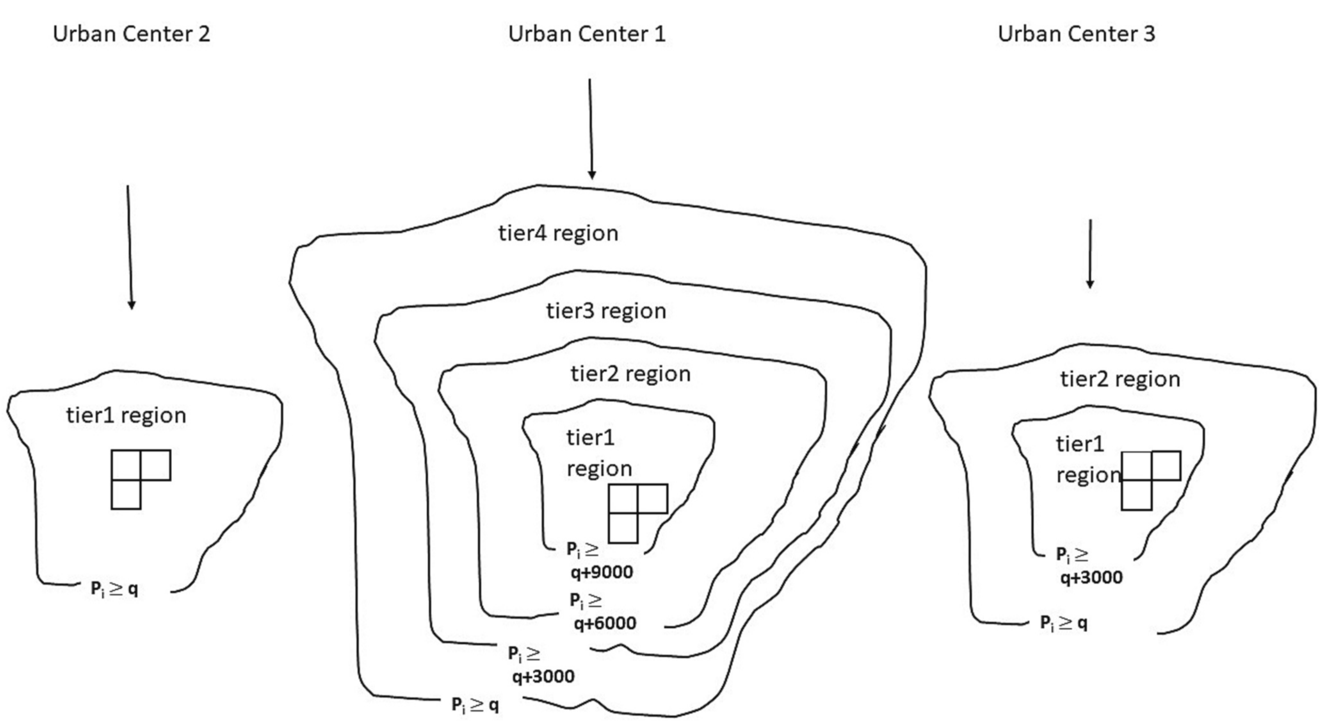

Fig. 1. Diagram of the identification of urban centers and sub-centers.

$$compact = pop_{center} / pop_{city} \tag{2}$$

$$balance = 1 - \frac{1}{2N^{*}pop_{center}}\left(\sum_{i}\sum_{j}|pop_{centeri} - pop_{centerj}|\right) \tag{3}$$

where *poly* is the polycentricity, *N* is the number of urban centers, and *compact* is the ratio of the population of the urban center; pop_{center} to the total urban population pop_{city}, which measures whether the population is more distributed in the urban center or scattered in the non-central area. *balance* is the size balance of urban centers, which measures the uniformity of the size of the urban center and is calculated by subtracting the traditional Gini coefficient from Eq. (1). In this formula $pop_{centeri}$ is the total population of the city center *i*. *var* is a continuous variable depicting the level of imbalance across different city centers; $var = 0$ means the city has only 1 center; *var* increases as other centers emerge and their sizes grow to be approaching the main center; if the size of each center in the city is the same, $var = 1$.

Recognizing the potential arbitrariness in setting thresholds for city centers, we conducted a robustness test to examine cities that were near the threshold of gaining or losing centers in specific years. In these instances, we simulate data randomization to nullify the increase or decrease of centers. The repeated randomization tests for cities in proximity to the threshold consistently yield results that align with the baseline regression. This suggests that the inherent arbitrariness in the thresholding process has negligible effects on the model outcomes. Detailed results from the robustness test are provided in Supplementary Materials Table A6-A8.

3.3. Measurement of urban economic efficiency

3.3.1. Input-output indicator selection for efficiency measurement

Data Envelopment Analysis (DEA) is an input-output method that is often used to measure different dimensions of urban efficiency, including urban economy efficiency (Yao et al., 2022), green development efficiency (Ma et al., 2019), infrastructure efficiency (Chen et al., 2019), and energy efficiency (Shah et al., 2022). It measures how efficiently production factors and resource inputs are utilized in producing the final outputs, by each of the decision-making units (DMU) that is represented by each of the prefectural-level cities in China. In this section, we identify the key input and output indicators that have been selected for estimating urban economic efficiency using the DEA method.

We follow the parsimonious principle for indicator selection of DEA-based economic efficiency measurement methods. Generally, the number of input indicators plus the number of output indicators is less than or equal to one-third of the number of evaluation units. Based on previous studies of urban efficiency (Chen et al., 2019; Ma et al., 2019; Yao et al., 2022; Zhou et al., 2018), this paper selects fixed assets, land resources, non-agricultural labor force, and technology as the city's input, and non-agricultural Gross Domestic Product (GDP) as the city's output to measure the city's economic efficiency. The fixed assets used for urban production are the fixed capital stock accumulated over a long period. The perpetual inventory method is used to calculate the fixed capital stock (Guo et al., 2022). This paper selects R&D expenditures as inputs, aligning with previous studies on entrepreneurial innovation (Zhou & Li, 2021). The specific measurement is derived in (4):

$$K_{i0} = \frac{I_{i0}}{g_0 + \delta}, K_{it} = K_{i,t-1}(1 - \delta) + I_{it} \tag{4}$$

where K_{i0} represents the stock of fixed capital in the benchmark year of the i^{th} city, I_{i0} represents the fixed capital investment in the benchmark year of the i^{th} city, and g_0 represents the growth rate of per capita GDP; δ is the depreciation rate, which is 6 % in this study; K_{it} represents the stock of fixed assets in the i^{th} city in the *t* period; I_{it} represents the fixed capital investment in the i^{th} city in the period, *t*. The labor force is defined as non-agricultural employment at the end of the year, while land input is measured by the total urban built-up area. R&D investment is expressed by the total annual amount. The variables and their summary definitions are provided in Table 1.

3.3.2. Super-slack-based measure (Super-SBM) model

The classical DEA models suffer two main limitations: 1) efficiency cannot be compared when there are multiple effective decision-making units; 2) lack of variables generated by input and output are not considered and may lead to biased estimations (Yao et al., 2022). This study applies a Super-slack-based model (hereafter, Super-SBM) proposed by Tone (2002) and later used by studies with similar goals (Chen et al., 2019; Ma et al., 2019; Zhou et al., 2018) to measure agglomeration economic efficiency using the identified input-output indicators. Two main steps are involved in the Super-SBM model; the first is to measure the efficiency of all decision-making units. The second step involves conducting super-efficiency measurements on all effective decision-making units.

Step 1: Assuming that the efficiency of *n* decision-making units needs to be measured, their input matrix is $X = (x_{ij}) \in R^{m \times n}$, output matrix is $Y = \left(y_{ij}\right) \in R^{s \times n}$, and they satisfy the condition that both input and output are positive, then their production may be set as $P = \{(x,y)|x \geq X\lambda, y \leq Y\lambda, \lambda \geq 0\}$. For each of the decision-making units (x_0, y_0) that represents the input-output relationship of a prefecture-level city, it should satisfy:

$$x_0 = X\lambda + s^{-} \tag{1}$$

$$y_0 = Y\lambda + s^{+} \tag{2}$$

Among them, λ, s^{-}, $s^{+} \geq 0$. $s^{-} \in R^{m}$, which means the input is redundant and $s^{+} \in R^{s}$ represents that output is insufficient. Define an index ρ:

$$\rho = \frac{1 - \frac{1}{m}\sum_{i=1}^{m}\frac{s_i^{-}}{x_{i0}}}{1 + \frac{1}{s}\sum_{i=1}^{s}\frac{s_i^{+}}{y_{i0}}} \tag{3}$$

The index ρ satisfies two properties: 1) the value range is between 0 and 1, and it is not affected by the change of output and input measurement units; 2) with the increase of input redundancy and output shortage. Thus, it is strictly monotonically decreasing and can be used to measure the efficiency of different decision-making units. The Super-SBM model seeks to minimize the index ρ under the condition that all the production constraints of the decision-making units are satisfied:

Table 1
Indicators of urban economic efficiency.

Urban efficiency indicators	Data sources
Output indicator	
GDP	Non-agricultural GDP (billion RMB)
Input indicator	
Labor force	The count of individuals employed in non-agricultural sectors per unit, measured at the end of the year (per 1000 employees).
Capital investment	Total value of fixed capital stock estimated through the perpetual inventory method (1000 yuan)
Land Resources	The total area of developed urban land, reflecting land resources dedicated to urban infrastructure and construction (million m^2)
R&D investment	Expenditures on science and technology initiatives, representing the financial commitment to research and development activities (1000 RMB)

$$\min \rho = \frac{1-\frac{1}{m}\sum_{i=1}^{m}\frac{s_i^-}{x_{i0}}}{1+\frac{1}{s}\sum_{i=1}^{s}\frac{s_i^+}{y_{i0}}}$$

$$x_0 = X\lambda + s^- s.t.$$

$$y_0 = Y\lambda + s^+$$

$$\lambda, s^-, s^+ \geq 0 \tag{4}$$

If the decision-making unit (x_0, y_0) in the current production has realized that redundant input and the production shortage are both 0, the ρ value is 1, which is the effective decision-making unit of the SBM, or say the city with the ideal production efficiency given its input resources and the corresponding outputs.

Step 2: Assuming that (x_0, y_0) is an effective decision-making unit of SBM, defining a production possible set that excludes (x_0, y_0) itself $P\backslash(x_0, y_0)$, and then define a production possible set $\overline{P}$, which is $P\backslash(x_0, y_0)$, a subset of all (x_0, y_0) decision-making units whose efficiency is not higher than:

$$\overline{\mathrm{P}} = \{(\overline{\mathrm{x}}, \overline{\mathrm{y}})|\mathrm{P}(\mathrm{x}_0, \mathrm{y}_0) \cap \{\overline{\mathrm{x}} \geq \mathrm{x}_0, \overline{\mathrm{y}} \leq \mathrm{y}_0\}\} \tag{5}$$

Define an index δ:

$$\delta = \frac{\frac{1}{m}\sum_{i=1}^{m}\frac{\overline{x_i}}{x_{i0}}}{\frac{1}{s}\sum_{i=1}^{s}\frac{\overline{y_r}}{y_{i0}}} \tag{6}$$

This index quantifies the economic distance between the remaining decision-making units (excluding the effective decision-making units of SBM) and the effective decision-making units of SBM. The more redundant the average input of the remaining decision-making units is or the more the average insufficient production is, the larger the δ is. The value δ is not <1, so it can be used to measure the efficiency of the effective decision-making unit of SBM. Specifically, the problems that the Super-SBM model needs to solve are:

$$\min \tau = \frac{1}{m}\sum_{i=1}^{m}\frac{\widetilde{x}_i}{x_{i0}}$$

$$\mathrm{s.t.}\frac{1}{s}\sum_{i=1}^{s}\widetilde{y}_r \Big/ y_{r0} = 1$$

$$\widetilde{x} \geq \sum_{j=1,\neq 0}^{n} \Lambda_j x_j$$

$$\widetilde{y} \leq \sum_{j=1,\neq 0}^{n} \Lambda_j y_j$$

$$\widetilde{x} \geq t x_0 \text{ and } \widetilde{y} \leq t y_0$$

$$\Lambda \geq 0, \widetilde{y} \geq 0, t > 0 \tag{7}$$

Solving this linear programming, the super-efficiency evaluation value of the decision-making unit is obtained, and its value range is larger than 0. The larger the value, the higher the efficiency.

3.4. Empirical strategy

After measuring the urban agglomeration efficiency, four panel regression models are set up to test the four hypotheses regarding urban polycentricity and agglomeration economy efficiency. In all four models, each prefecture-level or above city represents a polycentric or non-polycentric spatial unit (changing by the years) and is the basic DMU that has a production efficiency each year. The dependent variable in this study is agglomeration economy efficiency, while the independent variables include various measurements for polycentricity, as well as other control factors. Model 1 investigates hypothesis 1, namely, the non-linear impact of city i's polycentricity ($poly_{it}$) at time t on agglomeration economic efficiency. Quadratic and non-quadratic forms of polycentricity will be tested. The model specification is:

$$\mathrm{efficiency}_{it} = \beta_0 + \beta_1 \mathrm{poly}_{it} + X_{it}\beta + u_i + v_t + \epsilon_{it} \tag{8}$$

Where $efficiency_{it}$ is the urban agglomeration efficiency for city i at time t; X_{it} is a set of control variables to be explained in the next Section 3.4. u_i and v_t are the two-way fixed effects of year and city, respectively. Robust standard errors are used for all regressions.

Model 2 tests the second hypothesis, the impacts of city size and central city population density on the relationship between polycentricity and agglomeration economy efficiency. Specifically, variable pop_{it} and $density_{it}$ represent the population and central city density of city i at time t that will also interact with $poly_{it}$ to explore whether larger and more crowded cities would benefit more from polycentric urban structures. The model specification is:

$$\mathrm{efficiency}_{it} = \beta_0 + \beta_1 \mathrm{poly}_{it} + \beta_3 \mathrm{poly}_{it} {}^* \mathrm{pop}_{it} + X_{it}\beta + u_i + v_t + \epsilon_{it} \tag{9}$$

All other annotations and model settings are the same as those in Eq. (8). $density_{it}$ will also be examined as an alternative to pop_{it} and the interaction terms.

Model 3 compares the impacts on urban economy efficiency of different polycentric spatial configurations (H3), the size balance of urban centers $balance_{it}$, and compactness of urban centers $compact_{it}$, as well as the fourth hypothesis that evaluates whether city size and density interact with the number of city centers. It is similar to the non-quadratic form of Model 2, while $poly_{it}$ is replaced with the other spatial configurational measurements, and the interaction term is the number of city centers N_{it} and pop_{it} ($density_{it}$).

A potential endogeneity issue of the model arises from the possibility that the decision of a city to adopt polycentricity may be influenced by previous or current levels of urban agglomeration efficiency. For example, a national strategic masterplan to add an innovation (new industry) hub to a city would establish a new city center ("new town") while at the same time improving economic efficiency with the national investment of high-tech industry.

In the realm of studies investigating the relationship between urban form and economic growth, the inherent interconnectedness of these variables introduces endogeneity issues. To mitigate this challenge, we employed two well-established endogeneity test procedures. First, we embraced the methodology advocated by Li and Liu (2018) incorporating historical polycentricity. This entailed selecting a specific year, typically more than a decade before the examination point (in this study, it is designated as t-11 with an alternative test for t-3), to minimize the susceptibility of past polycentricity to reverse influences from "future" economic growth. Secondly, we utilized geomorphological features recognized for their strict exogeneity to economic growth. In the context of polycentricity studies, slope emerged as a frequently employed instrumental variable (IV) due to its exogenous nature, compelling certain cities to adopt a polycentric development pattern (Wang et al., 2019; Li et al., 2022; Li and Du, 2022). The instrumental model uses a 2-step least squares (2sls) method for estimation. Both sets of instrumental variables were applied in this study, producing consistent results, and the instrumental variable "historic polycentricity" successfully passed the identifiable test and the weak instrumental variable test. Consequently, it is reported as the primary result in this manuscript. Additional details and results from alternative tests are available in Supplementary Materials Table A3 to A4.

3.5. Variables and data sources

3.5.1. Model variables

Apart from the core dependent and independent variables, the other control variables in this paper include city-level industrial structure, public service, infrastructure, the extent of government intervention, and foreign capital utilization as well as dummy variables of city types. Most of the control variables are widely used for studies of urban economic efficiency (Chen et al., 2019; Chen et al., 2021; Li et al., 2020; Wang et al., 2021), though the dummy variables can use some more elaboration. In this paper, the dummy variable is to identify "shrinking cities", which have different explanations concerning polycentricity, as previous studies point out (Schmidt et al., 2021). A readily and convenient way to identify shrinking cities in China is to use the "resource-based city" categorization issued by the central government of China in 2013. There are four types of resource-based cities, and this paper employs a coding scheme with five categories to differentiate between non-resource-based and resource-based city types. Among the coding, resource-based city codes 3 ("resource-mature") and 4 ("resource-declining") are identified by previous studies as the main types of

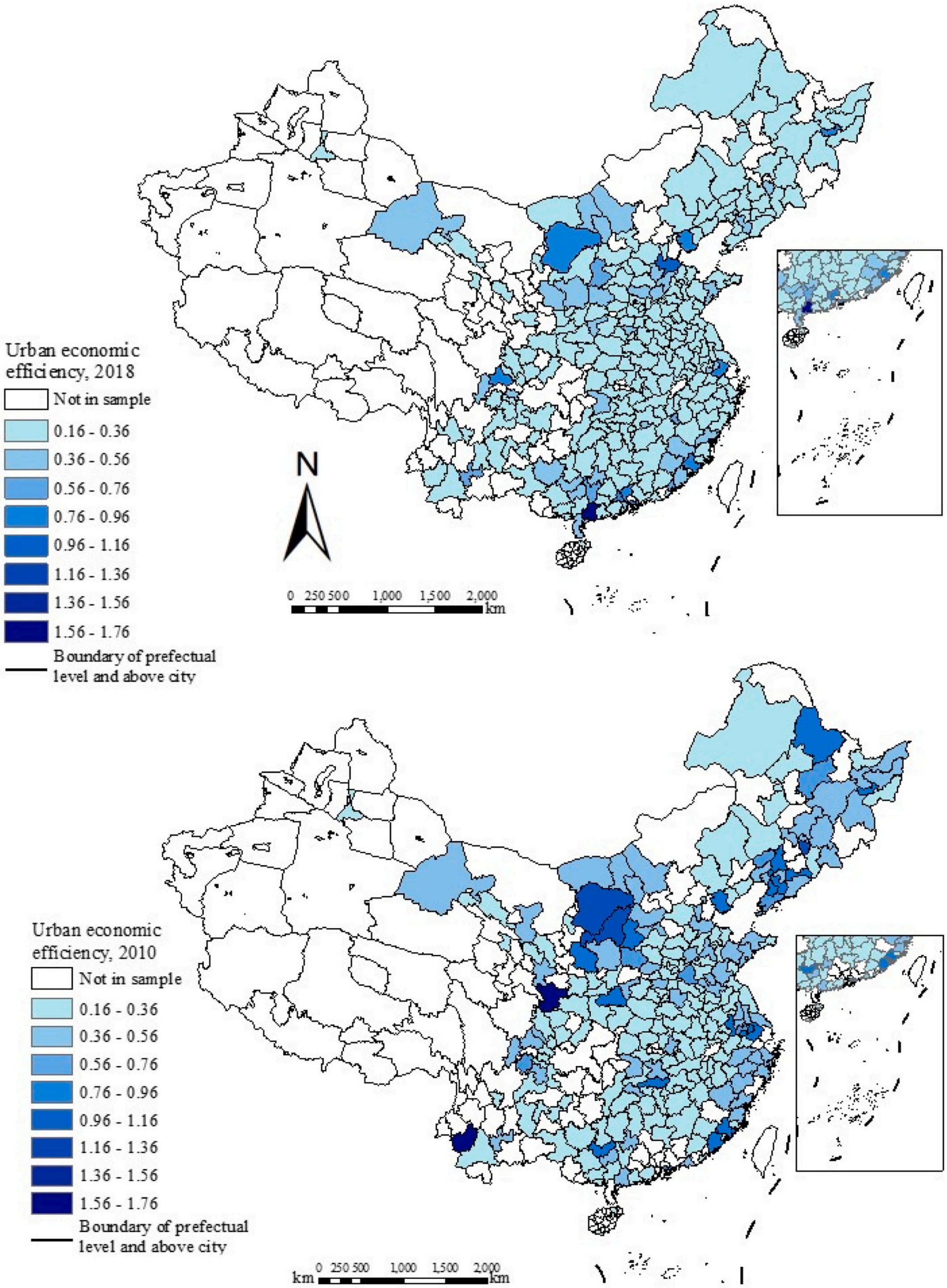

Fig. 2. City boundary and urban economic efficiencies in 2010 and 2018.

shrinking cities (Guo et al., 2021). The study by Schmidt et al. (2021) also points out the variations in polycentricity among different spatial directions of cities. Accordingly, this study uses another dummy variable to divide cities into four regions: eastern, central, western, and northeastern.

3.5.2. Data sources

China's geographical administrative structure is intricate, but among its various divisions, the category of "prefecture-level cities or above" stands out as the most straightforward and well-defined. Comprising 333 distinct and non-overlapping geographical units as of 2023, these entities collectively cover the entirety of China's territory. In alignment with established conventions in the study of city-level polycentricity in China (Li & Liu, 2018; Wang et al., 2019; Li et al., 2022; Li and Du, 2022), the sample in this study includes 252 prefecture-level cities or above, chosen for their consistency and availability of longitudinal statistical data, from year 2010 to 2018. Fig. 2 demonstrates the administrative units and their boundaries analyzed in this study. The boundary map (see Fig. 2) reveals a notable observation: certain prefecture-level cities, primarily situated in the north and west, encompass vast expanses of territory. This poses potential consistency challenges when comparing cities. In many instances, these expansive boundaries predominantly comprise non-inhabitable lands, such as forests, deserts, and mountains. The actual "urban areas" within these boundaries are more akin to those in other prefecture-level cities. To ensure comparability in our data collection and variable definition, we exclusively utilize data (about population, density, and areas) within the urban areas. Additionally, we exclude prefecture-level cities that are predominantly non-urbanized or lack data for their urban areas.

Measurement of polycentricity employs the LandScan high-resolution global population dataset, which is generated from a combination of census and night-time light imagery. Developed by the Oak Ridge National Laboratory (ORNL), this database contains 24-h average global population distributions with a resolution of approximately 1 km, taking a variety of factors into account, such as nighttime lighting, land use, and demographics. The dataset has been widely used to study population dynamics and urban form (Roy Chowdhury et al., 2018). The other data used in this study (including efficiency measurement and control variables) are taken from the China Urban Statistical Yearbook (2011–2019). Most of the data follow established procedures, while the population density of urban centers and direct use of foreign capital need some elaboration. The density of urban centers is obtained by dividing the total population of the central area identified by the LandScan dataset by the area of the central region. The real direct use of foreign capital is calculated using the average exchange rate of the year. The variables and their data sources are listed in Table 2 while Table 3 shows the descriptive statistics of the paper.

Table 2
Variables and Data Source.

Variable	Symbol	Unit	Data source and explanations
Dependent variable			
Urban Economic Efficiency	efficiency	n/a	Urban Economic Efficiency Measured by Super-SBM Model
Polycentricity			
Urban polycentricity	poly	n/a	Measured from LandScan Population Distritbuion with IRT-LI method
Control variables			
Urban population	pop	1 million people	LandScan dataset
Population density of central city	density	1000 people per km^2	LandScan dataset
Industrial structure	structure	ratio	Calculated as the ratio of the output value of the service (tertiary) industry to the output value of the manufacturing (secondary) industry, sourced from Chinese statistical yearbook.
Public service capacity	public	per 1000 people	Quantified as the ratio of the number of urban hospital beds to the population in the city, sourced from Chinese statistical yearbook.
Infrastructure level	infra	m^2 per 1000 people	Calculated as the ratio of road area to the population in the city (square meters/person)
Urban foreign capital utilization level	foreign	ratio	Represents the actual direct utilization of foreign investment concerning the city's GDP
Government intervention level	govern	ratio	Quantifies the extent of government involvement through the ratio of government fiscal expenditure to the city's GDP
City location cluster	region	categorical	1: Northeast; 2: West: 3: Central; 4: East
Shrinking and resource-based city	resource	categorical	0: Not shrinking or resource-based; 1: Renewable resource-based city; 2: Growing and resource-based city; 3. Non-growing and resource-based city; 4: Shrining and resource-based city.

4. Empirical results

Table 4 shows the overall estimation for the impacts of polycentricity on urban agglomeration economy efficiency. Among all the non-quadratic models examined, it was found that polycentricity does not have a significant impact on urban agglomeration economy efficiency. For the quadratic model, the base model indicates a U-shaped curve, while IV-2sls models have insignificant inference (at 10 % significance level) of *poly* and $poly^2$, suggesting that we cannot conclude that there are impacts of polycentricity on urban agglomeration efficiency, and there is not a simple optimum for overall polycentricity.

Table 5 shows the estimation for the influence of population and central city's density on the relationship between polycentricity and urban agglomeration economy efficiency. In terms of urban population, the interaction terms between population and polycentricity are significant and positive in the base model and the 11-year lag IV model; this outcome implies that polycentricity only improves agglomeration economy efficiency when the city size is larger. On the other hand, the coefficient for polycentricity is consistently negative across all models, and it is statistically significant in the base model. Taking this into account, the threshold of urban population scale over which polycentricity has positive impacts on efficiency can be calculated, and the threshold is 8.54 million and 3.93 million in the two models, averaging 6.24 million. In the 2017 sample, only 55 out of 252 cities in China met or surpassed this threshold.

The findings for central city density are similar to those for population and the implications are expected. All models have negative but insignificant estimates on the relationship between polycentricity and urban agglomeration efficiency, while only the 1-year lag IV model shows positive and significant interactions between the effects of polycentricity and population density. Based on the estimated coefficients, the density threshold of the central city for polycentricity to have positive impacts is 6061 people/km^2. 107 out of 255 sample cities in China meet or surpass the condition.

Table 6 shows the impacts of polycentric spatial configuration on urban agglomeration economy efficiency, and its interactions with population and density. More balanced size among urban centers and more compact configurations of each urban center both have in general

Table 3
Key variable descriptive statistics table.

Variables	Observations	Average	Sd.	Maximum	Minimum
Urban economic efficiency	2270	0.620	0.218	2.271	0.160
Urban polycentricity	2270	0.616	0.601	6.045	0.000
Urban population	2270	4.670	3.310	30.290	0.461
Population density of central city	2270	6.35	4.38	40.133	0.262
Industrial structure	2270	0.929	0.484	5.022	0.210
Public service capacity	2270	0.436	0.130	1.417	0.131
Infrastructure level	2270	0.429	0.3941	6.200	0.023
Urban foreign capital utilization level	2270	0.044	0.041	0.303	0.000
Government intervention level	2270	0.187	0.085	0.704	0.062

Table 4
Model 1 Results (Quadratic and non-quadratic model).

Non-quadratic model	Base	IV-2sls 3y-lag	IV-2sls 11y-lag
poly	−0.0202	0.0240	0.0297
	(0.0153)	(0.0184)	(0.0217)
R^2	0.269	0.207	0.207
N	2270	2268	2260
structure	YES	YES	YES
govern	YES	YES	YES
public	YES	YES	YES
infrastructure	YES	YES	YES
foreign	YES	YES	YES
pop	YES	YES	YES
city FE	YES	YES	YES
year FE	YES	YES	YES
resource		YES	YES
region		YES	YES
Quadratic model			
poly	−0.0540**	0.0444	0.0788
	(0.0272)	(0.0381)	(0.0481)
$poly^2$	0.0101**	−0.0058	−0.0150
	(0.0047)	(0.0075)	(0.0104)
R^2	0.271	0.207	0.203
N	2270	2268	2260
structure	YES	YES	YES
govern	YES	YES	YES
public	YES	YES	YES
infrastructure	YES	YES	YES
foreign	YES	YES	YES
pop	YES	YES	YES
city FE	YES	YES	YES
year FE	YES	YES	YES
resource		YES	YES
region		YES	YES

Note: Standard errors in parentheses; $*p < 0.1$, $** p < 0.05$, $*** p < 0.01$; the Base model is the OLS model with robust error; IV-2sls 3y-lag is the 2sls model with the 3-year lag of polycentricity as IV; IV-2sls 11y-lag is the 2sls model with the 11-year lag of polycentricity as IV.

positive impacts on efficiency. Both estimations yield positive and statistically significant results, except for the 3-year lag IV model with density as the interaction term. On the other hand, the interaction between population and density with the number of centers (N) is positive and significant in all models. This outcome implies that planning new urban centers is beneficial when the size and density of the existing

Table 5
Model 2 Results (Interactions of polycentricity with urban population and central city density.)

Urban population	Base	IV-2sls 3y-lag	IV-2sls 11y-lag
poly	−0.0515*	−0.0239	−0.0572
	(0.0271)	(0.0411)	(0.0443)
poly*pop	0.00603*	0.0787	0.01456**
	(0.00358)	(0.0566)	(0.00604)
structure	−0.0579	−0.0083	−0.0088
	(0.0432)	(0.0323)	(0.0327)
govern	−0.0307	−0.2035	−0.1906
	(0.1485)	(0.1780)	(0.1792)
public	0.0208	−0.0649	−0.0563
	(0.0660)	(0.0946)	(0.0966)
infrastructure	0.0009	0.0016	0.0016
	(0.0033)	(0.0042)	(0.0042)
dfi	−0.3482**	−0.5390***	−0.5605***
	(0.1614)	(0.1946)	(0.1941)
pop	−0.0917	0.0426	−0.0157
	(0.0943)	(0.0730)	(0.0753)
city fixed effects	YES	YES	YES
year fixed effect	YES	YES	YES
type of resource city		YES	YES
region		YES	YES
R^2	0.270	0.214	0.213
N	2270	2268	2270
Density of central city			
poly	−0.0267	−0.0201	−0.1274
	(0.0270)	(0.0539)	(0.0819)
poly*density	0.0094	0.0555	0.2102**
	(0.0235)	(0.0614)	(0.1067)
structure	−0.0590	−0.0105	−0.0085
	(0.0432)	(0.0326)	(0.0314)
govern	−0.0264	−0.1858	−0.1863
	(0.1484)	(0.1915)	(0.1964)
public	0.0293	−0.0492	−0.0077
	(0.0648)	(0.0943)	(0.0992)
infrastructure	0.0014	0.0002	−0.0001
	(0.0034)	(0.0045)	(0.0048)
foreign	−0.3408**	−0.5387***	−0.5236**
	(0.1606)	(0.2069)	(0.2057)
density	0.0145	−0.0057	−0.1171
	(0.0313)	(0.0560)	(0.0823)
pop	−0.0388	0.1006***	0.1013**
	(0.0958)	(0.0359)	(0.0397)
city fixed effect	YES	YES	YES
year fixed effect	YES	YES	YES
type of resource city		YES	YES
region		YES	YES
R^2	0.270	0.211	0.182
N	2270	2268	2270

Note: Standard errors in parentheses; * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$; the Base model is the OLS model with robust error; IV-2sls 3y-lag is the 2sls model with the 3-year lag of polycentricity as IV; IV-2sls 11y-lag is the 2sls model with the 11-year lag of polycentricity as IV.

urban centers meet or surpass certain criteria. The threshold for urban population is 7.66 million and 18.08 million, and the threshold for central city density is 6914 people/km^2. These thresholds are higher than the thresholds for polycentricity to be beneficial. This is in general understandable, as planning more centers would require stricter conditions than just being polycentric.

5. Discussion and policy takeaways

5.1. Discussion

The findings of this paper suggest that there is no "one-size-fits-all" rule for whether polycentricity can benefit urban agglomeration efficiency. This finding is consistent with previous evidence that the relationship between polycentricity and urban agglomeration efficiency is inclusive and sometimes even negative (Li et al., 2019; Li & Liu, 2018;

Table 6
Model 3 results (spatial configuration of polycentricity and agglomeration economy efficiency).

	IV-2sls 3y-lag (population)	IV-2sls 11y-lag (population)	IV-2sls 3y-lag (density)	IV-2sls 11y-lag (density)
balance	0.1278*	0.3430**	0.1141	0.2889*
	(0.0715)	(0.1650)	(0.0710)	(0.1544)
compact	0.1296	0.5712***	0.1076	0.3789*
	(0.1777)	(0.2186)	(0.1758)	(0.2215)
N	−0.0036	−0.0094*	−0.0177**	−0.0202**
	(0.0043)	(0.0050)	(0.0071)	(0.0090)
N*pop	0.00047*	0.00052**		
	(0.00027)	(0.00025)		
N*density			0.00256***	0.00273***
			(0.00078)	(0.00097)
density	0.0493	0.0314	−0.1295*	−0.1462*
	(0.0510)	(0.0528)	(0.0663)	(0.0782)
pop	0.0642	0.1478*	0.1219**	0.1688**
	(0.0744)	(0.0806)	(0.0564)	(0.0668)
structure	−0.0128	−0.0321	−0.0135	−0.0219
	(0.0354)	(0.0355)	(0.0297)	(0.0297)
govern	−0.2104	−0.2027	−0.1969	−0.2070
	(0.1934)	(0.2008)	(0.1876)	(0.1931)
public	−0.0259	−0.0654	−0.0141	−0.0227
	(0.1020)	(0.1116)	(0.0993)	(0.1072)
infrastructure	−0.0015	−0.0039	0.0001	−0.0013
	(0.0045)	(0.0048)	(0.0045)	(0.0046)
foreign	−0.5487***	−0.5481**	−0.5495***	−0.5275***
	(0.2115)	(0.2249)	(0.1969)	(0.2037)
city FE	YES	YES	YES	YES
year FE	YES	YES	YES	YES
resource	YES	YES	YES	YES
region	YES	YES	YES	YES
R^2	0.215	0.173	0.229	0.203
N	2268	2270	2268	2270

Note: Standard errors in parentheses; * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$; Base model is the OLS model with robust error; IV-2sls 3y-lag is the 2sls model with the 3-year lag of polycentricity as IV; IV-2sls 11y-lag is the 2sls model with the 11-year lag of polycentricity as IV.

Wang et al., 2019). In the context of China, polycentricity in many cities is planned and built in the form of new towns and/or industrial parks to facilitate land-financed state revenue and accumulation (Wang, 2022). The new-town constructions are progressively located farther away from the city centers, with a decline in planned density. In some cases, these new towns have even become known as "ghost cities" (Xu, 2022). The debt-financed new towns are also generating decreasing investment returns (Han et al., 2021). Thus, irrationally motivated polycentricity does not reduce agglomeration diseconomies, and in many cases hurts agglomeration economy efficiency and also becomes an inefficient utilization of land resources and capital.

To justify and identify the suitable conditions for polycentric development, this study points out that high urban population and central city density are the prerequisites for planning efficient polycentricity. Furthermore, this relationship is more obvious for the number of city centers than the extent of polycentricity—which means that adding new urban centers requires stronger scrutiny and prudence. Intuitively, larger, and more densely populated urban centers suffer more severe congestion and environmental issues, while they have stronger radiation to better connect with sub-centers. The thresholds found in this study for positive impacts of polycentricity are also quite considerable: over 6 million people and 6000 people/km^2. For smaller and less populated countries and cities, such thresholds are particularly favorable for the development of city regions where polycentric clusters can encompass numerous closely located cities and metropolises. This is especially applicable in the context of the European Union (EU) (Bartosiewicz & Marcińczak, 2020; Lee & Shin, 2012).

As for the spatial configurations, the most important finding for urban planners is that planners are that compact urban form is the preferred choice for urban centers and sub-centers. Though initiated from a different literature lineage, compactness and polycentricity have been increasingly discussed together as potential solutions to urban challenges. For example, principles like polycentricity, compact development, and transit development together can reduce commuting time in large urban centers (Jun, 2020). Thus, polycentricism with multiple compact centers is the direction for metropolitan areas' development.

The size hierarchy of multiple urban centers presents a complex challenge. The findings of this study indicate that sub-centers should have comparable sizes and even be on par with the main city center to optimize efficiency. Though studies have reasonably supported decentralized and specialized sub-centers to form a more distinct hierarchy of polycentric urban systems (Vasanen, 2012; Yu et al., 2022), our findings suggest that each of the sub-centers should have full and similar functions and sizes in comparison to the main urban center. In this way, long commuting times between multiple centers can be minimized, and more diversified functions within each center can increase its resilience to environmental, economic, and social shocks.

5.2. Policy takeaways

This study has several policy takeaways for urban planners and policymakers. First, the study underscores the limitations of treating polycentricity as a universal solution for urban planning, highlighting its inadequacy in addressing challenges and optimizing agglomeration urban efficiency across all cities and urban regions. Instead, the application of polycentricity policies and planning is recommended to be specific to mega-cities and mega-city regions, particularly those with a population exceeding 6 million and a central city density surpassing 6000 people/km^2. This targeted approach aims to avoid the pitfalls associated with a one-size-fits-all strategy and advocates for tailored strategies based on the unique size and characteristics of each city and urban region.

Specifically, for smaller urban agglomerations in western and central China, the study cautions against pursuing multi-center development, aligning with previous evidence (Yang et al., 2023). It emphasizes that the full agglomeration economies of central cities may not have been realized in such cases. Adopting a polycentric strategy through top-down state planning and investment, such as new and distant industrial parks to existing urban centers, and real estate development to stimulate land financing, may lead to negative consequences, including higher government debt and wasteful use of land resources, ultimately resulting in agglomeration efficiency loss.

For mega-cities and mega-city regions, the study's emphasis on specific criteria, including a population exceeding 6 million and a central city density surpassing 6000 people/km^2, underscores a thoughtful consideration of the requisite scale and intensity for successful polycentric implementation. It is crucial to emphasize that enhancing the agglomeration economy efficiencies of mega-cities or mega-city regions should not be pursued solely for the sake of a polycentric form. Instead, urban planning should integrate complementary policy instruments, such as compact development and urban renewal. This comprehensive approach aims to concentrate human capital, facilitate knowledge communication, and promote infrastructure sharing within mega-cities while mitigating dis-economies associated with congestion and pollution through polycentric development (Yao et al., 2021).

6. Conclusions

This study demonstrates a method that identifies urban structure with the major shift away from a single central business district (CBD) dominant city, as well as a stark dichotomy of city and suburbs (Hewings & Parr, 2007; Lucas & Rossi-Hansberg, 2002). With sub-centers identified at any density peaks within the city and polycentricity measured by different indicators, this study empirically examines the relationship between urban polycentricity and agglomeration economy efficiency, as well as the more efficient spatial configuration of compactness. On the one hand, concerning the relationship between polycentricity and agglomeration efficiency, the findings suggest that there is no clear relationship (linear or non-linear) between polycentricity and agglomeration efficiency when all cities in the sample are considered. On the other hand, the evidence suggests that polycentricity is associated with an enhancement in agglomeration economy efficiency, particularly in the context of cities that are large and dense enough. This relationship is noticeable when the population exceeds approximately 6 million, and the central city density reaches over around 6000 people/km^2.

In exploring the spatial configuration aspect, our analysis suggests a potential correlation between the beneficial aspects of agglomeration economy efficiency and two factors: the compactness in density across all centers and a balanced size distribution among multiple centers within a city or city region. Additionally, an observed trend indicates that increasing the number of centers is recommended only in the presence of large and dense cities, with the population and density thresholds being marginally higher than those associated with the promotion of polycentricity.

The study has several limitations. Firstly, it is essential to avoid overly simplistic assumptions about direct links between policy decisions and their effects. While polycentricity has often been a pursuit in Chinese planning from a top-down perspective, it is crucial to acknowledge that economic efficiency may not always be the sole or primary objective. Numerous intervening variables and diverse goals could potentially yield conflicting evidence. For instance, research by Li and Du (2022) and Yao et al. (2022) underscores the importance of considering environmental efficiencies associated with polycentricity, introducing additional complexities to the analysis. Secondly, though connectivity between centers is reflected in our spatial configuration measurements of polycentricity, they are not explicit. There are further opportunities to apply network measures in addition to the cell-based measurements of polycentricity. Ultimately, while prior city-level studies in China generally support the utilization of prefectural-level city boundaries (Li & Liu, 2018; Wang et al., 2019; Li et al., 2022; Li and Du, 2022), we acknowledge that the inconsistency in city sizes poses challenges to the validity of results when measuring urban forms such as polycentricity. To address this concern moving forward, it is crucial to consider emerging big data as a more reliable proxy for city delineation than relying solely on administrative boundaries for assessing polycentricity. Notable examples of such big data sources include mobile phone data, human mobility data (Boeing, 2021; Lv et al., 2021; Pan et al., 2018), and social media interaction data (Zhen et al., 2017).

CRediT authorship contribution statement

Haozhi Pan: Writing – review & editing, Writing – original draft, Investigation, Formal analysis, Data curation. **Yongling Yao:** Writing – review & editing, Validation, Supervision, Resources, Funding acquisition, Conceptualization. **Yue Ming:** Writing – original draft, Software, Methodology, Investigation, Formal analysis, Data curation. **Zhou Hong:** Writing – review & editing, Visualization, Software, Formal analysis, Data curation. **Geoffrey Hewings:** Validation, Supervision.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.cities.2024.104884.

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