The impact of polycentric development on regional gap of energy efficiency

A Chinese provincial perspective

Zou, Yanfen; Lu, Yuhai ; Cheng, Yang

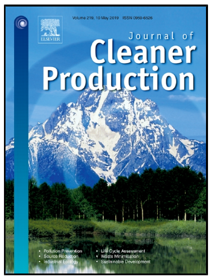
Published in:
Journal of Cleaner Production

DOI (link to publication from Publisher):
10.1016/j.jclepro.2019.03.285

Publication date:
2019

Document Version
Accepted author manuscript, peer reviewed version

Accepted Manuscript



The Impact of Polycentric Development on Regional Gap of Energy Efficiency: A Chinese Provincial Perspective

Yanfen Zou, Yuhai Lu, Yang Cheng

PII:	S0959-6526(19)30996-5
DOI:	10.1016/j.jclepro.2019.03.285
Reference:	JCLP 16289
To appear in:	*Journal of Cleaner Production*
Received Date:	17 September 2018
Accepted Date:	26 March 2019

Please cite this article as: Yanfen Zou, Yuhai Lu, Yang Cheng, The Impact of Polycentric Development on Regional Gap of Energy Efficiency: A Chinese Provincial Perspective, *Journal of Cleaner Production* (2019), doi: 10.1016/j.jclepro.2019.03.285

The Impact of Polycentric Development on Regional Gap of Energy Efficiency: A Chinese Provincial Perspective

Yanfen Zou[1], Yuhai Lu[2], Yang Cheng[*1, 3]

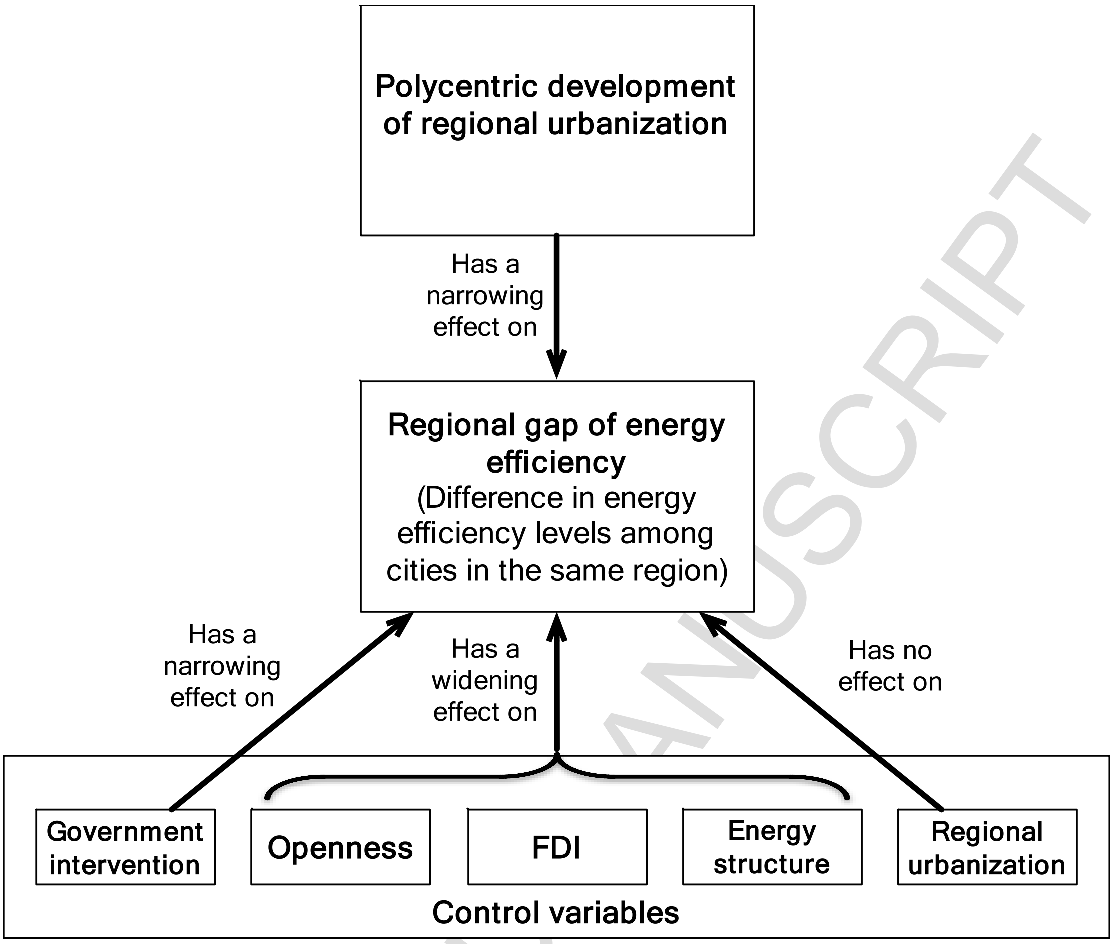
1: School of Business Administration, Jiangxi University of Finance and Economics
Nanchang, Jiangxi Province, China
2: Modern Economics & Management College, Jiangxi University of Finance and Economics
Jiujiang, Jiangxi Province, China
3: Center for Industrial Production, Department of Materials and Production, Aalborg University
Aalborg, Denmark
* Corresponding author, Email: cy@business.aau.dk

Abstract: A reasonable distribution of urban systems is essential for optimizing spatial energy allocation and the quality of economic growth for China. This study discusses the impact of the polycentric development on the regional gap of energy efficiency (RGEE), i.e. difference in energy efficiency levels among cities in the same region, in the Chinese provincial context, by employing a novel method using nighttime lighting data from Defense Meteorological Satellite Program's Operational Linescan System (DMSP/OLS) to measure the spatial structure of provinces and Stochastic Frontier Approach (SFA) to evaluate the total-factor energy efficiency. Our results firstly show that the polycentric development has a narrowing effect on the RGEE. Second, they show that the more government intervention can narrow the RGEE of a province, but being more open, having more foreign direct investment (FDI), and using more coal can widen the RGEE of that province. Meanwhile, the level of regional urbanization is shown to have no influence on RGEE. Third, they show that the polycentric development has a negative effect on the energy efficiency of large cities, but a positive effect on that of small and medium size cities, which accordingly narrows the RGEE. The conclusions of this study not only reveal insights for policies that aim to reduce the RGEE, but also provide an empirical basis for future urban development strategies in the Chinese provincial context.

Keywords: urbanization model; polycentric development; regional gap of energy efficiency; satellite light data

Acknowledgments: The work was supported by the National Social Science Fund of China (No.16BJY085), the Natural Science Fund of China (No.71764009), the National Statistical Fund of China (No.2015LZ37), and the Technology Fund of Jiangxi Province Education Department (No.GJJ151605). Besides, it was also supported by Sino-Danish Research Center.

Graphical abstract



The Impact of Polycentric Development on Regional Gap of Energy Efficiency: A Chinese Provincial Perspective

Abstract: A reasonable distribution of urban systems is essential for optimizing spatial energy allocation and the quality of economic growth for China. This study discusses the impact of the polycentric development on the regional gap of energy efficiency (RGEE), i.e. difference in energy efficiency levels among cities in the same region, in the Chinese provincial context, by employing a novel method using nighttime lighting data from Defense Meteorological Satellite Program's Operational Linescan System (DMSP/OLS) to measure the spatial structure of provinces and Stochastic Frontier Approach (SFA) to evaluate the total-factor energy efficiency. Our results firstly show that the polycentric development has a narrowing effect on the RGEE. Second, they show that the more government intervention can narrow the RGEE of a province, but being more open, having more foreign direct investment (FDI), and using more coal can widen the RGEE of that province. Meanwhile, the level of regional urbanization is shown to have no influence on RGEE. Third, they show that the polycentric development has a negative effect on the energy efficiency of large cities, but a positive effect on that of small and medium size cities, which accordingly narrows the RGEE. The conclusions of this study not only reveal insights for policies that aim to reduce the RGEE, but also provide an empirical basis for future urban development strategies in the Chinese provincial context.

Keywords: urbanization model; polycentric development; energy efficiency gap; satellite light data

1. Introduction and theoretical background

During the last 40 years, as a result of reform and development, the urbanization rate of China has grown from 10.64% in 1978 to 58.52% in 2017. This development of "urban China" has changed the country's economic geography, reconstructed the framework of the urban system, and thus become an important part of China's modernization. China's future strategy involves establishing a more effective mechanism for regional coordination and development and constructing an urban pattern of coordinated development for cities with different size (Qi and Luo, 2007; Zhu and Xia, 2018).

Along with this development, more energy has been consumed in the urban areas of China. As indicated by the first version of "China urban energy report" published in 2018[1], the urban areas consume 85% of total energy annually produced in China today, 18 percent higher than the world's average level. Therefore, it has become extremely important to address the impact of the development of urbanization on energy consumption, and further on energy efficiency, especially due to international pressure from Climate Change Agreements and the need for green development (Wu et al., 2018; Mohammadi & Ram, 2017). Accordingly, much research has been conducted to validate the direct quantitative relationship between urbanization level and energy efficiency for different time periods and backgrounds (Shahbaz & Lean, 2012; Yan, 2015; Liu & Shao, 2015; Cheng, 2016; Sun et al., 2017). The research generally suggested the positive effect of urban spatial agglomeration on energy efficiency, leading to the proposition of the famous agglomeration effect and crowding effect regarding the spatial development of urbanization (Ang and Choi, 1997; Au & Henderson, 2006; Li & Li, 2010; Al-Mulali et al., 2013; Sadorsky, 2013; Elliott et al., 2017; Bilgili et al., 2017). There were certainly other studies indicating the negative or the nonlinear effect of urban spatial agglomeration on energy efficiency, such as Liu & Xie (2013), Shi & Shen (2013), Rafiq et al. (2016), Wang et al. (2018), among others. Nonetheless, in either situation, the spatial development of urbanization is expected to contribute significantly to the improvement of energy efficiency in the Chinese context, if managed properly (Cheng, 2016). Such contribution has, to some extent, been confirmed by the urbanization development of China in the past years. As indicated in the first version of "China urban energy report", the energy consumption per GDP has decreased by around 65%, from 2.8 times higher than the world average level in 1990 to 1.4 times higher in 2017.

Although energy efficiency has generally been improved along with the spatial development of urbanization in China, the energy efficiency between cities in different stages of development (even in the same regions) has become significantly different. The difference in terms of energy consumption per GDP is 6.6 times between the cities with highest energy consumption per GPD and the ones with lowest in 2017. The energy consumption per GDP of some Chinese cities in the post industrialization stage, such as Beijing, Shanghai, Guangzhou, and Shenzhen, is far lower than the average level of China and it can even be comparable to that of cities in developed countries. This phenomenon has also been verified by the recent research, such as Ma & Stern (2008), Wang et al. (2013), Zhao et al. (2013), Pan et al. (2014), Zhang (2015), and Chen et al. (2016), showing regional energy efficiency exhibits a certain degree of (absolute and conditional) convergence (at the provincial level) in China. Thus, it becomes imperative in the Chinese context to address the

[1] The first version of "China Urban Energy Report" released by China Energy News on 2018-10-19, http://www.china-neng yuan.com/news/130280.html.

relationship between the spatial development of urbanization and the regional gap of energy efficiency (RGEE), which is defined as the difference or convergence in energy efficiency levels among cities (in the same region). Certainly, much research has been conducted to better understand the reasons behind the RGEE, although they might name RGEE in other terms. These studies provide very useful insights for understanding the causes behind the RGEE by identifying different impact factors, including economic development, marketization degree, human capital, technological progress, industrial structure, and government regulation (Alcantara & Duro, 2004; Ezcurra, 2007; Qi et al., 2009; Liddle, 2010; Chen et al., 2013; Pan et al., 2013; Duro, 2015; Li et al., 2015; Ma et al., 2015; Zhao, et al., 2015; Zhang et al., 2015; Elliott et al., 2017; Jiang, et al., 2017; Li et al., 2017; Mohammadi & Ram, 2017; Deichmann et al., 2018). See Table 1 for their details.

Table 1: Details of the existing studies addressing the impact factors of RGEE

Reference	Sample size & data type	Geographic scope	Dependent variable	Estimation method	Impact factors and significance
Qi et al. (2009)	81 Panel data	China, and 8 developed countries	Difference of energy intensity	Regression	Industrial structure (-0.1175) Energy price (-0.1662***) Fixed asset investment (-0.1493***) Technology progress (-0.1532**) Per capita GDP (1.55***) FDI (0.0105**)
Jiang et al. (2017)	1088 Cross-sectional data	China	Deviation of energy intensity	IDA (index decomposition analysis) model Sensitivity analysis	Industrial structure (-0.1521 to 2.2390) Export structure (-0.0001 to 0.0544)
Elliott et al. （2017）	540 Panel data	China	Energy intensity, electricity and coal intensity	Mean group estimation	Urbanization1 (1.392*** to 2.011***) Urbanization2 (1.345*** to 2.255***) Per capital GDP (-0.803*** to -1.517***) Industrial structure (1.865*** to 3.517***) Transportation (-0.149 to 0.629*)
Li et al. (2015)	120 Panel data	China	Energy intensity	GLS regression	Openness (-0.028*** to -0.036***) Government intervention (0.255*** to 0.262***) Industrial structure (0.207 *** to 0.238***) Energy price (-1.448*** to -1.504***) Technology progress (-0.117*** to -1.317***)
Alcantara & Duro (2004)	870 Panel data	30 OECD Countries	Theil index of energy intensity	Theil index	Technology progress Industrial structure (Just analysis, no computation)
Liddle (2010)	3996 Panel data	111 Countries (1971-2006); 134-country (1990-2006)	Coefficient of variation (CV)， Kernel density	Regression	Industrial structure Technologies progress Energy structures (Just analysis, no computation)
Ezcurra (2007)	3038 Panel data	98 countries	The standard deviation of the logarithms (SDlog) (CV) of primary energy intensity	Non-parametric approach	Industrial structure Transportation (Just analysis, no computation)

Ma et al. (2015)	390 Panel data	China	σ and *β* convergence of energy intensity	System GMM	Industrial structure (-0.1305* to 0.0040) Per capita GDP (-0.0001 to 0.1207***) Urbanization1 (-0.0986*** to 0.1137***) Energy price (-0.2881*** to -0.0728**) Technology progress (-3.1040 to 0.8111)
Zhao et al. (2015)	180 Panel data	China	σ and β convergence of total factor energy efficiency	DEA-Bootstrap, Panel data model	Energy structure (-0.1066** to -0.3026***) Industrial structure (0.1962** to 0.2416**) Government intervention (0.1137 to 0.2819***) Openness (0.4304*** to 0.5722***) FDI (0.0000***) Economic growth (0.2325 to 0.0893)
Pan et al. (2013)	784 Panel data	China	Total factor energy efficiency, energy intensity	DEA, Panel tobit regression	Technology progress (-2039.81*** to 1738.40***) Per capita GDP (2.92 to 11.70***) Energy structure (32.99 to 3.37***) Marketization (-1.80 to 16.62***)
Li et al. (2017)	784 Panel data	China	Energy and CO2 emissions performance	Regression, DEA, Non-radial directional distance function	Openness (0.0233*** to 0.0411***) Energy price (-0.675 to 0.0490) Human capital (0.0035*** to 0.0042***) Government intervention (-0.457*** to 0.253***)
Duro (2015)	3014 Panel data	137 countries	CV, Gini coefficient, and the Theil index of energy intensity	Panel data model	Per capita GDP (0.80 to 0.95) Economic growth (-1.12 to 0.57)
Zhang et al.（2015）	128 Panel data	China	*β* of energy intensity	Panel quantile regression	Industrial structure (1.945*** to 2.527***) Per capita GDP (-0.493*** to -0.616***) Energy structure (0.002*** to 0.003***) Technology progress (-0.011*** to -0.016)
Deichmann, et al. (2018)	3425 Panel data	137 countries	Aggregate energy intensity	Piecewise regression	Industrial structure (0.39*** to 0.78***) Openness (0.00***) Population density (0.00***) Non dependent population Share (exclude aged 15–65) (-0.01** to 0.00) Per capita GDP (-0.26*** to -0.68***)
Chen et al. (2013)	330 Panel data	China	Energy productivity	β tests	FDI (0.0022 to 0.2079**) Technology progress (0.0675 to 0.0076)
Mohammadi & Ram (2017)	2112 Panel data	48 US States	Per capita energy use	CV, and β, σ, and γ, and Stochastic tests, Barro-type regressions	No *β*-convergence and γ-convergence; Lack of ***σ***-convergence and stochastic convergence

However, to our best knowledge, the spatial development perspective has been much ignored in this discussion (Wan et al., 2015; Guo & Sheng, 2017; Liu, 2017). We do not currently know much about whether and how the spatial development of urbanization influences the REEG. Most of the existing studies merely addressed the relationship between the spatial development of urbanization and regional energy efficiency, rather than RGEE (Zhang, 2003; Meijers & Burger, 2010; Cheng, 2011; and Yuan & Li, 2015). We only identify Song & Zhou (2017), which indirectly explored the relationship between the spatial development of urbanization and RGEE. Nevertheless, it is time to address such a relationship now. The first stage of China's urbanization, which includes land and population expansion, is almost complete (Qin et al., 2013). The next step is to ensure effective control of urbanization within the region, explore the potential to spatially narrow the regional gap, and improve living standards (Kim, 2015; Zhang et al., 2017). An effective spatial development of urbanization that conforms to energy and environmental policies is expected to contribute to the improvement of RGEE, and further the realization of the second stage of China's urbanization.

In fact, the spatial development of urbanization is generally expressed in terms of the spatial distribution of the population (Swyngedouw et al., 2002; Henderson, 2003). There are normally two development models that regions can follow to recreate regional urban spatial structures for their urbanization: monocentric and polycentric. The former refers to the fact that almost all the population is concentrated in a single central city, whereas the latter assumes that the population is distributed evenly into multiple central cities in one region (Kontuly and Dearden, 2003; Su et al., 2017). In the last decade, the polycentric development model of urbanization has generally been accepted by Chinese cities (Rafiq et al., 2016; Huang, 2005; Zhang & Yue, 2017). Intuitively, this development model could be more useful if aiming to narrow the RGEE and make the regions developing in a balance manner in terms of energy efficiency (Yan and Sun, 2015; Yuan and Li, 2015; Zhang et al., 2017). However, in-depth analyses on the relationship between the polycentric development model of regional urbanization and RGEE remain scarce and the impact of the polycentric development on RGEE has yet been verified, as most of the research on the impact of polycentric development has been limited to economic growth and income disparity (Giuliano et al., 2016; Garcia-López, et al., 2013; Wei & Chen, 2016; Liu et al., 2017). Thus, this paper aims to bridge this gap. Specifically, it applies regression analysis to explore the relationship between polycentric development and RGEE, where it uses the nighttime light data released regularly by the National Geographical Data Center of the National Oceanic and Atmospheric Administration to measure polycentric development of Chinese provinces, the data obtained from various statistical yearbooks to evaluate total-factor energy efficiency based on Stochastic Frontier Approach (SFA), and further coefficient of variation of energy efficiency to represent RGEE.

The remainder of this paper is structured as follows. First, in Section 2, we demonstrate the relationship between the polycentric development model of regional urbanization and RGEE from a theoretical perspective and develop the research hypothesis accordingly. Afterwards, the research methodology is introduced in Section 3. Furthermore, we test the developed hypothesis and present the empirical analysis regarding the influence of polycentric development on the RGEE in Section 4. The results of the analysis are further discussed in Section 5, where polity implications are also suggested. We conclude this paper by summarizing the findings and indicating the limitations in Section 6.

2. Hypothesis development

The polycentric development model of urbanization describes a relatively balanced population distribution among different cities in one region (Sun & Song, 2017). Its main aim is to solve the problems of excessive population concentration in the main and central cities, disorder development, rapid expansion, and resource waves through effective evacuation and balance (Meijers & Burger, 2010; Burger et al., 2014). It allows modern urban planning to move beyond the idea of a single center and to promote a large spatial network with a polycentric city area. In this study, the impact of polycentric development on the RGEE can be elaborated on the basis of the following theories of urban development.

2.1 Theory of agglomeration economy

The dynamic agglomeration economy theory holds that the negative externality of agglomeration can lead to inefficiency when the agglomeration scale exceeds a certain value (Williamson, 1965). This means that, during later periods of economic development, elements might be redistributed within the region under the full flow of elements, and economic activities might become decentralized to narrow the gap between regions (Hanson, 1996; Qin et al., 2013). Relevant empirical studies have also confirmed the above speculation. Henderson (2003) and Brulhart & Sbergami (2009) concluded that each area has its own optimal scale after examining different regions using the urban primary index. Population concentration can be enhanced when the scale is smaller than the optimal point, while larger scale might have a congestion effect, restraining economic growth (Chang and Brada, 2006). The European Spatial Development Perspective (ESDP) released by the European Commission in 1999 stated that a polycentric and network urban development model is more conducive to regional balance in Europe by reducing internal differences. Accordingly, polycentric development has become a policy target and a focus of research in European countries. With improvements in traffic, polycentric urban networks can completely extend the geographic space of a single large central city to reduce uneconomic agglomerations (Phelps and Ozawa, 2003; Jahansson and Quigley, 2004; Luo et al., 2011) and form dynamic externalities because manufacturers in sub-central cities can avoid the high costs of the central area while enjoying the benefits of an agglomeration economy (Anas et al., 1998; Li et al, 2014). Zhou & Ma (2000) and Su et al. (2017) also indicated that the polycentric model could effectively alleviate uneconomic agglomeration of a central city during urbanization through expansion in the initial stage to promotion in the middle and advanced stages for China. During the development, efficient factor (re)allocation tends to balance the spatial value and narrow regional gaps, including the RGEE (Sovacool, 2011).

2.2 Theory of size borrowing

The size borrowing theory, originally conceptualized by Alonso (1973), suggests that closely linked small cities have equal function to a similar sized large city because of their geographical proximity. One example can be the satellite areas of large cities along the Atlantic coast. Meanwhile, the polycentric spatial structure can also lead to the *size borrowing* effect within a region (Phelps, et al., 2001), and the benefits of economic scale and agglomeration can be achieved within a larger geographical space (Liu et al., 2017). Nevertheless, the polycentric model during the advanced stage of urbanization is not a simple low-density dispersion but a re-concentration of scale and labor division (Sun & Song, 2017). Chen (2012) showed that clusters can form a functional and cooperative system with highly interactive commuters under the support of rail transport system and internet technology, despite being separated in space. It is also expected that the polycentric spatial development model can improve the level of factor flow and market integration and accelerate technology spillover and knowledge sharing between cities within a region. All these are expected to further contribute to narrowing the RGEE (Luo et al., 2011; Han et al., 2014).

2.3 Theory of central place

The *central place theory* advocated by new economic geography emphasizes that regional urban polycentric evolution can effectively promote the specialized division of labor cooperation, regional cooperation, and balance productivity layout to reduce the energy efficiency gap between adjacent regions and achieve overall improvement (Meijers, 2007; Meijers & Burger, 2010; Wei et al., 2016; Song & Zhou, 2017). Nevertheless, under the dual track system of China's current resource allocation, resources in one province can become overly concentrated in a few cities rather than being driven by the inherent requirements of scale economies (Li et al., 2014; Su et al., 2017). Moreover, the incentive mechanism of "competition for growth" can hinder the transfer of related industries across regions and causes an imbalance between insufficient investment and labor outflow in peripheral areas, leading to the expansion of regional disparities (Zhang et al., 2014; Xu, 2016). In this case, it makes more sense to follow the regional polycentric development to avoid the low efficiency caused by an excessive concentration of resources, as demonstrated by the development of modern American cities (Meijers, 2007). In other words, comprehensive large cities need to be more responsible for e.g. the industrial production of innovative laboratories, so that specialized small and medium-size cities can benefit from greatly reduced production costs and become a hub for mature industries (Duranton and Puga, 2001). This further results in a "win-win situation" among all cities in the region, promoting economic growth of small and medium-size cities and reducing the RGEE (Luo, 2010; Qin et al., 2013).

Based on the above analysis, as well as considering the dynamic geo-economic theory, the polycentric development policy of ESDP, and current urbanization in China, we propose the hypothesis for this study, i.e. polycentric urban spatial development can narrow the RGEE.

3. Methodology

3.1 Measurement of polycentric development

The degree of polycentric urban spatial development in a region can be measured using demographic data at the urban level. However, statistical disagreements occur because of the discontinuity of resident population data and frequent size adjustments during the measurement period. To address this issue, the previous studies suggested that satellite-based nighttime light datasets derived from the Defense Meteorological Satellite Program's Operational Linescan System (DMSP/OLS) can be used as a reasonable alternative to population space distribution and urban spatial structure (Donaldson & Storeygard, 2016; Liu et al., 2017; Zhao et al, 2018), as they provide uniform, spatially explicit, continuous, and timely observations and measurements of human activity related to settlement changes and socioeconomic dynamics (Ma et al, 2012). To some extent, nighttime light data can better reflect the development of urbanization, since urbanization normally refers to the population shift from rural to urban residency and the gradual increase in the proportion of people living in urban areas. People can commute to work at one place in daytime, but not live there. Therefore, substantial studies have focused on exploring the relationship between nighttime light signals and regional socioeconomic activity through constructing various nighttime light indices. They have generally proved the significant positive correlations between DMSP/OLS nighttime light brightness and demographic and socioeconomic variables, such as urban extent for urbanization dynamics, spatiotemporal changes, and urbanization patterns (Ma et al., 2012;

Kamarajugedda et al., 2017; Tan et al, 2018; Zhao et al., 2018). Therefore, we use DSMP/OLS nighttime light data to measure the regional polycentric development according to the method of Liu et al. (2017), in order to overcome the shortcomings of statistical data.

Specifically, in this paper, regional polycentric development is measured by the Pareto index of urban size distribution, which has the following formula:

$$\ln p_{it} = C - q_t \ln R_{it} \tag{1}$$

where p_{it} is the nocturnal value of nighttime light brightness in city i in year t, C is a constant, and R_{it} is the rank of the nocturnal luminance value of city i in the province in year t. After ranking the total lighting brightness of each city in the province from large to small, according to the regression (equation 1), coefficient q can be obtained to determine the polycentric index. When q>1, the population in the province is more dispersed, indicating the typical distribution of a polycentric spatial structure; when q<1, central cities in the province are dominant, indicating a single center distribution. It should be emphasized that our study uses the method of Meijers & Burger (2010) to make the measured polycentric index comparable among different provinces. The top two, three, and four cities in a province are regressed for the polycentric level, before taking the average of q obtained from these three regressions (Liu et al., 2017).

3.2 Measurement of RGEE

The single-factor and total-factor methods are usually applied to calculate energy efficiency. The former only uses energy factors as the input, without considering other production elements such as energy intensity (Qi et al., 2009; Jiang et al., 2017; Elliott et al., 2017), energy productivity (Deichmann, et al. 2018), and per capita energy use (Chen et al., 2013; Meng et al., 2013; Mishra and Smyth, 2014), whereas the latter considers various input factors (Pan et al., 2013; Zhao et al., 2015; Zhang et al., 2017). Because a single index is not comprehensive enough to consider the substitution effect of other input indicators, the efficiency measure is generally based on the theory of multi-factor production function (Proskuryakova & Kovalev, 2015; Bo et al., 2016). Therefore, the total-factor method is employed in this paper to evaluate the energy efficiency, especially given the lack of generality and flexibility associated with parametric methods (Ezcurra, 2007; Mohammadi & Ram, 2017).

The methods to calculate the total-factor energy efficiency include non-parametric methods, of which the classic is Data Envelopment Analysis (DEA) proposed by Farrell (1957), and parameter methods that determine production functions, including Cobb-Douglas (C-D) production functions, Constant Elasticity of Substitution (CES) production functions, and transcendental logarithmic (Translog) production function . Among the parameter methods, Stochastic Frontier Approach

(SFA) is the most widely used one (Sun, 2002; Wang, 2012). Compared with the DEA method, SFA can explain the random perturbation term and provide results that are closer to reality. Therefore, we choose SFA to measure the total-factor energy efficiency in this paper.

In the existing studies (such as Tao & Wang, 2011; Simon-Elorz et al., 2011), SFA is normally defined as:

$$y_i = f(x_i, \beta) \times \exp(v_i - u_i) = f(x_i, \beta) \times \exp(v_i) \times \exp(-u_i) \tag{2}$$

where y_i is the output vector, x_i is the input vector, β is the technology vector, and the first error term $v_i \sim N(0, \sigma_v^2)$ is a random error term, indicating the effect of various random factors on the front yield with non-controllability, such as unpredictable consumption and observation errors. The second error term $u_i \geq 0$ is a unilateral error term measuring the non-effectiveness of technology, which includes controllable influences such as technological backwardness and resource misallocation. $f(x_i, \beta)$ is the product function, where $f(x_i, \beta)\exp(v_i)$ represents a random frontier standard line: if $u_i = 0$, the point reflecting the producer's condition is on the front line; if $u_i > 0$, the point reflecting the producer's condition is lower than the point on the front line. The production function used in SFA generally takes the forms of the C-D product function, Translog product function, linear production function, Leonidov production function, or CES product function. Among them, the first two are most commonly used.

The form of production function required by the SFA model of total factor energy efficiency is described in detail below. We follow the work of Zhou (2012) and Chen (2017) by assuming that, in the framework of neoclassical sector production, capital (K), labor (L), and energy (E) are the inputs, and gross production (Y) is the output. The possible production function is thus conceptually represented as follows:

$$T = \{(K, L, E, Y) : (K, L, E) \text{produce } Y\} \tag{3}$$

In production theory, T is assumed to be a bounded and closed set, and the inputs and outputs can meet strong disposability, which means that, if $(K', L', E') \geq (K, L, E)$and $Y' \leq Y$, $(K', L', E', Y') \in T$. Assuming that there are *n* types of decision portfolio in terms of K, L, and E, (K_j, L_j, E_j, Y_j) is the output vector, corresponding to *j* type of decision portfolio (*j*= 1, 2, ..., n). Then, the Shephard energy distance function of the decision-making unit can be expressed as $D_E(K_j, L_j, E_j, Y_j)$. From the perspective of production efficiency, the SFA model is used after the specific production function is selected. The Translog production function is chosen in this paper because it is flexible and can reduce the risk of an incorrect production function (Griffin and Gregory, 1976). According to the definition of energy efficiency based on the Shephard energy distance function from Zhou (2012), the inefficiency of labor and capital is separated from the production function to construct the SFA model of total-factor energy efficiency. Taking all above into consideration, the function represented by formula (3) can be further written as:

$$\begin{aligned}\ln(1/E_{jt}) = \beta_0 + \beta_K \ln K_{jt} + \beta_L \ln L_{jt} + \beta_Y \ln Y_{jt} \\ + \beta_{KL}\left[\ln K_{jt} \times \ln L_{jt}\right] + \beta_{KY}\left[\ln K_{jt} \times \ln Y_{jt}\right] + \beta_{LY}\left[\ln L_{jt} \times \ln Y_{jt}\right] \\ + \beta_{KK}\left[\ln K_{jt}\right]^2 + \beta_{LL}\left[\ln L_{jt}\right]^2 + \beta_{YY}\left[\ln Y_{jt}\right]^2 + v_{jt} - u_{jt}\end{aligned} \tag{4}$$

where v_{jt} is the random error term and u_{jt} is a one-sided error term, which are independent of each other. Their distribution assumptions are: $v_{jt} \sim iidN(0, \sigma_v^2)$, $u_{jt} \sim N^+(0, \sigma_u^2)$, respectively. The maximum likelihood method (ML) is used to estimate the coefficients of each parameter, the SFA function and efficiency influence function, and the energy efficiency values of each decision unit in each year. Then, the energy efficiency (EE) is:

$$EE_{jt} = \exp(-u_{jt}) \tag{5}$$

The RGEE refers to the different degree of energy efficiency between cities in a region. In order to eliminate the influence of the levels of energy efficiency in different regions, it is measured by the coefficient of variation (CV) in this study (Liddle, 2010), and can be calculated as follows:

$$CV = \frac{\sigma}{\overline{EE}} \tag{6}$$

where CV is the RGEE: the greater the value, the bigger the RGEE among the cities in one region. σ is the standard difference of energy efficiency and $\overline{EE}$ is the mean energy efficiency.

3.3 The choice of control variables

We decide to follow the study of Besagni & Borgarello (2018) to choose the control variables for this study. After analyzing relevant literature that discusses the impact factors of RGEE, it is possible to identify 18 factors, as shown in Table 1. Nevertheless, we choose to integrate two factors, i.e. formal and informal urbanization, into one, i.e. urbanization rate (Elliott et al., 2017). Besides, we replace two other factors, i.e. non-dependent population share (aged 15-65) and export structure with human capital and Trade intensity. Accordingly, we end with 15 factors as shown in Table 2. Afterwards, we follow the suggestion of Besagni & Borgarello (2018) to conduct the analysis composed by OLS method, to determine the relationship between the identified factors and

RGEE, VIF, to check for multicollinearity, and least absolute shrinkage and selection operator (LASSO), to select significant predictors. The results are displayed in Table 2.

Table 2: The results of Aggregate regression model

Impact factors on RGEE	Description	Coef.	Std.Err.	T-value	P>|t|	Sig.	VIF
Industry structure	The second industry value proportion of GDP	0.0689	0.0856	0.80	0.422		2.32
Energy price	Fuel power category purchase price index	-0.0001	0.0005	-0.25	0.799		1.23
Fixed asset investment	Total investment in fixed assets of the whole society	0.0152	1.52e-06	-1.71	0.088	*	10.62
Technology progress	Public investment in science and technology/GDP	0.0248	0.0152	1.63	0.105		1.14
Foreign direct investment (FDI)	The proportion of foreign direct investment of GDP	0.9559	2.1965	0.44	0.664		4.16
GDP per capita	Regional total GDP/ Regional total population	1.21e-06	6.76e-07	1.79	0.074		10.06
Government intervention	The proportion of government expenditure to GDP	0.2265	0.0694	3.26	0.001	***	2.39
Energy structure	Coal consumption/Total energy consumption	0.0314	0.0124	2.54	0.012	**	1.63
Openness	Total amount of import and export/regional GDP	0.3280	0.0471	6.98	0.000	***	9.18
Transportation	Cargo volume	-1.31e-06	2.33e-06	-0.56	0.576		4.11
Human capital	The proportion of students at school to the total population	4.55e-06	2.75e-06	1.65	0.099	*	4.37
Urbanization	The proportion of the urban population to the total population	-0.1415	0.0611	-2.32	0.021	**	4.39
Economic growth	The growth rate of regional GDP	0.0027	0.0015	1.74	0.084	*	1.33
Marketization	Market integration degree index	-0.0003	0.0004	-0.65	0.517		1.89
Population density	Population/regional era	1.44e-09	4.39e-10	3.29	0.001	***	5.35

According to the rule of VIF<3, seven factors, i.e. government intervention, marketization, industrial structure, technology progress, economic growth, energy price, energy structure, are chosen for further analysis. Among these factors, only energy structure, economic growth, and government intervention are shown to have significant relationships with RGEE (at least p<0.1). Therefore, they are input into the calculation for R^2_{adj} in turn according to their significance from high to low, i.e. following the sequence of government intervention, energy structure, and economic growth. According to the rule of $R^2_{adj} < 5\%$, government intervention and energy structure are finally kept. For eight factors that have their VIFs higher than 3, i.e. openness, FDI, GDP per capita, urbanization, fixed asset investment, human capital, transportation, and population density, they are further analyzed based on LASSO, due to their multicollinearity. In fact, higher VIF generally suggests ordinary OLS might bring over-fitting issue. One way of addressing this issue is to introduce a penalty, when minimizing the residual sum of squares (RSS). In order to do so, the data set has to be divided into K parts, for the purpose of detecting the stability of the algorithm. Among K parts, K-1 parts are taken as the training data while the other part as the test data for experiments. Each test will yield the correct or error rates. Specifically, the K-fold approach (K=10) is adopted to calculate Mean Squared Prediction Error (MSPE), which in our case is 0.00036 as minimum. Corresponding to this MSPE, the optimal results of LASSO estimation can be further calculated for the eight factors mentioned above. As shown in Table 3, only the coefficients of openness, urbanization, and FDI derived from LASSO estimation are not zero, while the coefficients of other five factors are (this is also why they are not shown in the table). These results are further verified by the coefficients derived from Post-test OLS.

Table 3: Coefficients derived from LASSO estimation and Post-test OLS

Factor	LASSO	Post-test OLS
Openness	0.3022	0.3925
Urbanization	-0.0768	-0.0844
FDI	0.0632	0.0816

Consequently, we keep the five following factors as control variables: X1 (OPEN) indicates openness, i.e. the degree of opening up to the outside world, measured by the total regional import and export/regional GDP (Ang and Choi, 1997; Deichmann et al., 2018; Zhang & Lahr, 2014); X2 (FDI) indicates foreign direct investment, measured by the proportion of foreign direct investment of GDP in a year (Liao et al., 2007; Liu & Shen, 2010; Wiese et al., 2018); X3 (URB) indicates the level of regional urbanization, measured by the proportion of the urban population to the total population (Backlund et al., 2012; Wu, 2012; Sadorsky, 2013; Chen & Sun, 2017); X4 (GOV) indicates the degree of government intervention in economic activities, measured by the proportion of government expenditure to GDP (Backlund et al., 2012; Dütschke et al., 2018); and X5 (EST) indicates energy structure, measured by the proportion of coal consumption to the total energy consumption (Zhao et al., 2015; Duro, 2015).

3.4 Data source

Nighttime light data has been released regularly by the National Geophysical Data Center of the National Oceanic and Atmospheric Administration since 1992. Of the 34 photos obtained up to 2013[2], differences appear between photos from the same year because of the different sensors, which are shown as the sum of Digital Number (DN) values of bright pixels or different DN values for bright pixels in the same location between images. In addition, the lighting images selected in this study are all-year-round composite images across the world. Thus, continuity and saturation correction of the pixel DN values between lighting images are performed using the invariant target region method based on the administrative division of a fixed year (2011) to extract lighting data on different geographic scales for each year. Furthermore, we exclude four municipalities that are directly under the control of the central government: Beijing, Shanghai, Tianjin, and Chongqing, as well as Tibet, Qinghai, Xinjiang, and Hainan, due to a lack of data. Accordingly, this paper ends with using other 23 provinces of China as the sample. Specifically, the nighttime light data of these provinces from 1997 to 2013 are taken into analysis.

Regarding the calculation of total-factor energy efficiency based on the SFA model, the output variable is expressed as the regional GDP of each province, while three types of input factor are capital (K), labor force (L), and energy consumption (E). Because there is no official capital stock data currently published in China, the method of sustainable inventory is widely used to estimate the input factor capital (K). Therefore, we use the perpetual inventory method of Shan (2008) to estimate the capital stock of sample provinces based on the provincial data from the Statistical Yearbook of China regarding the fixed asset investment and fixed asset investment price index of society. For the labor force input index (L), most literature does not consider the quality difference of the employed population. In this study, the product of the number of employees and the average years of education is used to express the labor force input in order to highlight the difference in human capital level of different labor forces. The number of employees is equal to the average number of employees at the end of last year and this year. The average years of education is

[2] Data sources: National Night Light Index, Geographic Situation Detection Cloud Platform, http://www.dsac.cn/DataDownLoad.

$AL = \sum_{J=1}^{5} N_J * Ny_J \Big/ \sum_{J=1}^{5} N_J \; (J = 1,2,...,5)$, where N_J indicates the number of people who have not attended primary school, junior high school, senior high school, tertiary education, or above, and N_{yJ} indicates the average cumulative years of education for all types of education, categorized as 0-year, 6-year, 9-year, 12-year, and 16-year (Zhou, 2012; Honma and Hu, 2014; Chen, 2017). The number of employees at the end of the years in each region comes from the statistical yearbooks of each province, while the number of people with all types of education in each region comes from the Yearbook of Population and Employment Statistics of China for the corresponding years. Energy consumption (E) is expressed as the total energy consumption of a province, which includes primary energy (such as primary coal, crude oil, natural gas, hydropower, nuclear energy, wind energy, solar energy, geothermal energy, biomass energy), secondary energy products converted from primary energy (such as coal washing, coke, gas, electricity, heat, and oil), and other fossil energy, renewable and new energy. The relevant energy consumption data of 23 Provinces and 274 cities from 1997 to 2013 are obtained from the Energy Statistics Yearbook of China and the Compilation of 60 Year Statistics of New China. The other data regarding regional GDP, fixed asset investment, and fixed asset investment price index data for all society, as well as all control variables, are all obtained from the annual China Statistical Yearbook. Specifically, the actual utilization of foreign capital and total imports and exports are converted into RMB values at the current exchange rate, while the other value indexes are expressed at the current price because their values are not affected by the price factor after the relative ratio.

4. Empirical analysis

4.1 Model Setting

In order to verify the causal relationship between polycentric development and the RGEE, the empirical regression equation is used as follows:

$$CV_{It} = C + \alpha \ln q_{It} + \beta \ln X_{It} + u_I + v_t + \varepsilon_{It} \tag{7}$$

where CV represents the RGEE; I denotes the province; t represents the year (from 1997 to 2013); α and β are the discrete coefficient of energy efficiency in the region; q represents the polycentric index; and X represents other control variables that may affect the RGEE as identified above. C is a constant term; u_I and v_t represent the individual unobservable heterogeneity and the unobservable factor over time respectively; and ε_{It} represents the random error term. It should be noted that the lag number is set to 1–3 periods in order to eliminate potential endogeneity.

4.2 Data preparation

The study estimates the total factor energy efficiency of provinces using the SFA model through Frontier 4.l. The descriptive statistics of the polycentric level and total-factor energy efficiency of each province and principal function SFA are shown in Table 4. It is clear that most coefficients in the model passed at least the 10% significance level test. We hypothesize that the rejection value of γ is 0 at the level of 1% significance, meaning that the error term of the model exists as a compound structure with a random error term and a one-sided error term. R is 0.9471, indicating that 94.71% of the errors from stochastic frontier production functions are due to technical inefficiency, while the remaining 0.01% are due to uncontrollable random factors. Therefore, SFA is suitable for estimating production functions with high reliability.

Table 4: Descriptive statistics for polycentric index (q) and energy efficiency (EE) of provinces in the period from 1997 to 2013

	Mean value	Standard deviation	Minimum	Maximum
q	1.2820	0.6821	0.5627	4.1873
EE	0.6616	0.2015	0.2419	0.9876
	Variable	Parameter estimation	Variable	Parameter estimation
	Constant term	0.1997***(0.09923)	$\ln K \times \ln Y$	-0.3664***(0.07229)
	$\ln K$	-0.6756***(0.08389)	$\ln L \times \ln Y$	-0.6121**(0.4875)
SFA	$\ln L$	-0.1367***(0.08652)	$[\ln K]^2$	-0.7701(0.8628)
Main Function	$\ln Y$	0.1108***(0.08501)	$[\ln L]^2$	-0.2110**(0.1089)
	$\ln K \times \ln L$	0.2115*(0.06073)	$[\ln Y]^2$	0.4762***(0.09770)
	σ^2	0.0559***(0.0026)	γ	0.9471***(0.0261)
	Logarithmic likelihood value -12.8261			

***p<0.01, **p<0.05, * p<0.10. The standard deviation is the same in parentheses.

As shown in Table 4, the degree of polycentric development of China in the period from 1997 to 2013 is in the range between 0.5627 and 4.1873, with the average being 1.2820. In this period, different provinces in China tended to adopt different altitudes towards their polycentric development. As illustrated in Figure 1, the province with the biggest change in terms of its degree of polycentric development is Guangdong, dropping from 4.1873 in 1997 to 2.6577 in 2013. In contrast, the smallest change can be seen in Shanxi Province. Besides, a gradient decrease regarding the degree of polycentric development can generally be observed from coastal to inland provinces. The inland provinces tend to be more monocentric, while the coastal provinces tend to be more polycentric. Nevertheless, the degrees of the polycentric development seem to be more diverse with the standard deviation being 0.8921.

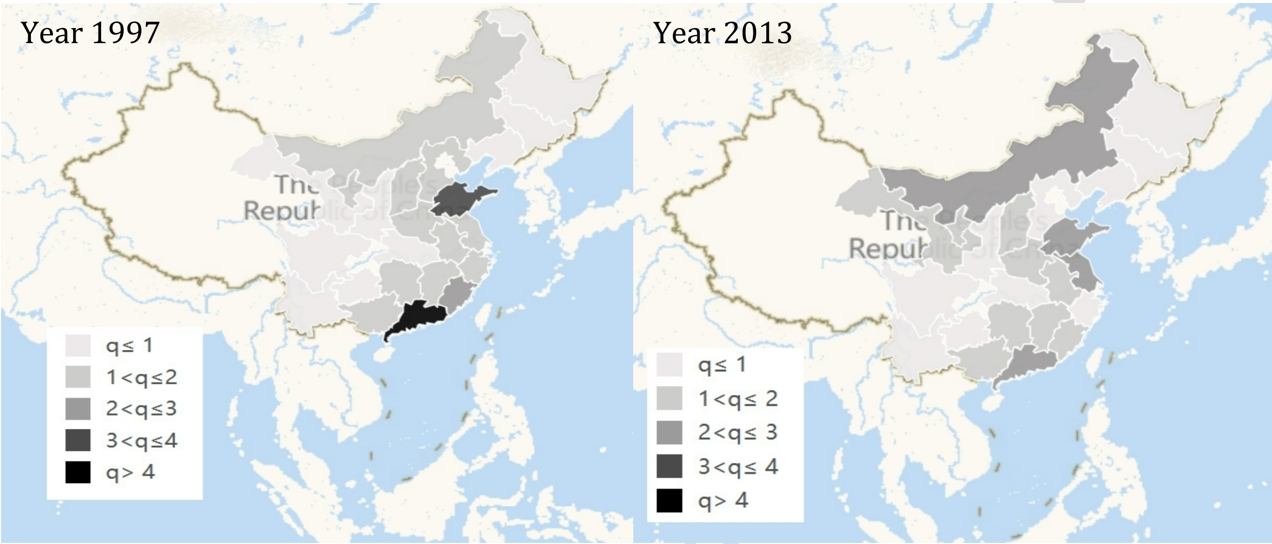


Figure1: The polycentric level of areas in China

4.3 Basic regression analysis

In this study, the fixed effect (FE) model and the random effect (RE) model are used for regression analysis of the model (equation 8), and the results are shown in Table 5. According to the results of the Hausman test, the fixed effect model should be selected here. Furthermore, we follow Chen (2014) to model regional and year effects as dummies. The regression coefficients of the polycentric index are significantly negative for both the single index and that with control variables (Table 5), which indicate that improvement in the degree of polycentric development within a province can effectively reduce the RGEE of that province. Columns (1)-(3) in Table 5 show that, on average, for every 10 percentage increase in the polycentric index, the RGEE will be reduced by 0.00367–0.00787. Thus, the current network externality of the polycentric urban system forms gradually, the urbanized agglomeration economy has a moderate influence beyond the boundary of a single city, and the RGEE decreases. Meanwhile, the regression coefficients of five control variables used in this study are generally consistent with expectations. At a statistically significant level of 1%, the coefficients of OPEN are significantly positive, but the coefficients of GOV are significantly negative. The other two control variables, namely FDI and EST, are all shown to have a positive relationship with RGEE at a statistically significant level of 10%. Only the influence of URB on RGEE is shown insignificant.

Table 5: Impact of polycentric development on the RGEE for provinces in the period from 1999 to 2013

	(1) FE	(2) RE	(3) FE	(4) RE
lnq	-0.0787*** (0.0576)	-0.0558*** (0.0274)	-0.0367 *** (0.0139)	-0.0164 (0.0131)
OPEN			0.0789***(0.0272)	0.1153***(0.0269)
FDI			0.0086* (0.0052)	0.0083(0.0053)
URB			0.0012 (0.0124)	0.0031 (0.0126)
GOV			-0.0568*** (0.0164)	-0.0583*** (0.0149)
EST			0.0125*(0.06118)	0.0079 (0.0061)
Year effect	YES	YES	YES	YES
Regional effect	YES	YES	YES	YES
R^2	0.1166	0.1161	0.1839	0.3455
Amount of observations	322	322	322	322
Hausman	chi2(2)=10.21		chi2(7)=32.47	
Test	Prob>chi2 =0.0902		Prob>chi2 = 0.000	

***p<0.01, **p<0.05, * p<0.10. The standard deviation is the same in parentheses.

4.4 Robustness test

Although Table 5 shows that the polycentric development can significantly reduce the RGEE, three shortcomings remain that might have the impact on the robustness of the results (Liu et al., 2017). The first shortcoming is related to the selection of the lag period for the explanatory variables, which is set to 1–3 periods. Second, a deviation can be inevitable, if the measurement of provincial polycentric development is completely dependent on the Pareto index of the distribution of urban scale. Third, there are actually different measurements for the RGEE and the polycentric index, which might also affect the robustness of the results. Therefore, we further evaluate our results by changing the lag period of the explanatory variables and the measurement of the RGEE and the polycentric development. Table 6 reports the regression results of the robustness test according to the above considerations.

Table 6: Robustness test for provinces in the period from 1999 to 2013

	(1)	(2)	(3)	(4)(theil)	(5)(atkinson)
ln*q*	-0.0392***(0.0129)			-0.0033 (0.0059)	-0.0102(0.0104)
ln*H*		-0.1139*(0.0617)			
ln*Poly*			-0.1213 (0.0766)		
Controlled variable	YES	YES	YES	YES	YES
Year effect	YES	YES	YES	YES	YES
R^2	0.1113	0.0043	0.0358	0.0418	0.1051
Amount of observations	253	322	322	322	322

***p<0.01, **p<0.05, * p<0.10. The standard deviation is the same in parentheses.

In Table 6, column (1) shows the results after all explanatory variables being lagged by four periods. The regression coefficient of the polycentric index is significantly negative at a level of 1%, which suggests that the replacement of lag periods does not change the previous results. Columns (2) and (3) show the results of the regression using the modified Herfindahl index (1n*H*) and the first degree index of the transformation (1n*Poly*) to replace the polycentric index '*q*', respectively (Liu et al., 2017), which also suggest that replacing the polycentric index does not change the results. Column (4) and column (5) show the results of the regression using the Theil index and Atkinson index of energy efficiency as explanatory variables, respectively. The coefficients are all negative, indicating that changing the measurement index of the RGEE does not affect the regression results.

4.5 Additional analysis

The results of this study indicate that a polycentric spatial development model can narrow the energy efficiency gap for cities within a region. As larger cities normally have higher energy efficiency in China, we propose that this gap reduction might be due to one of the three situations: (1) if polycentric development leads to an overall improvement in urban energy efficiency, then it must improve the energy efficiency of large cities more slowly than that of small and medium-size cities; (2) if polycentric development leads to an overall decline in urban energy efficiency, then the energy efficiency of smaller cities must decrease more slowly than that of larger cities; (3) if the effect of polycentric development differs for cities with different size, it must reduce the energy efficiency of large cities while improving that of small and medium-size cities. Based on these three assumptions, we use cities with different size from each region as the sample and energy efficiency as the dependent variable, and construct the following empirical regression model:

$$\ln EE_{it} = C + \alpha \ln q_{it} + \beta \ln X_{it} + u_i + v_{it} + \varepsilon_{it} \tag{8}$$

where the explained variable *EE* is the regional total-factor energy efficiency and *q* is the polycentric index. Specifically, the effects of polycentric development on energy efficiency in large and small and medium-size cities are examined respectively. Nevertheless, it should be noted that, on the one hand, only the data of 274 cities in the period from 2005 to 2013 is used for this analysis due to the data availability. On the other hand, small and medium-size cities in a region are not strictly defined in specific regressions. Instead, we follow a specific approach introduced in Table 7 to rank the cities in terms of their urban population size from large to small. Based on the rankings, the corresponding data is further input into equation (9) for regressions. The results are shown in Table 7.

Table 7: Impact of polycentric development on energy efficiency levels for large and small and medium-size cities (ranked by population size) in the period from 2005 to 2013

	Metropolis		Small and middle-size cities		
	Ranking<=3	Ranking<=4	Ranking>3	Ranking>4	Ranking>6
	(1)	(2)	(3)	(4)	(5)
lnq	-0.1443**(0.0588)	-0.1733***(0.0526)	0.0485*(0.0327)	0.1149**(0.0585)	0.1239*(0.0725)
Controlled variable	YES	YES	YES	YES	YES
Year effect	YES	YES	YES	YES	YES
Regional effect	YES	YES	YES	YES	YES
R^2	0.0060	0.0068	0.0011	0.0001	0.0050
Amount of observations	621	828	1845	1638	1224

***p<0.01, **p<0.05, * p<0.10. The standard deviation is the same in parentheses.

"Ranking<=3" represents the top three cities according to urban population; "ranking<=4" is the top four cities according to urban population; "ranking>3" refers to cities ranked after the top three according to urban population; "ranking>4" is cities ranked after the top four according to urban population; and "ranking>6" indicates cities ranked after the top six according to urban population.

As shown in Table 7, columns (1) and (2) show the regression results of the top three and four largest cities. Columns (3) to (5) show the results of all other small and medium size cities except the top three-, four-, and six-largest cities. It is clear that the polycentric spatial structure has a negative effect on the energy efficiency of large cities, at the significant level of 1%, but a positive effect for small and medium size cities at the significant level of 10% or above. In addition, for the top three and four cities, their regional energy efficiency decreases by 0.1443% and 0.1733% respectively, for each increase in the polycentric index. Conversely, for all other small and medium size cities except the top three-, four-, and six-largest cities, the inhibitory effect might converge and the regional energy efficiency increases by 0.0485%, 0.1149%, and 0.1239% respectively. A "U" structure can accordingly be observed along with declining city ranking. In other words, our results support the third path, i.e. the effect of polycentric development differs for cities with different size, and it reduces the energy efficiency of large cities while improving that of small and medium-size cities. However, this conclusion might not be true when ranking the cities according to economic scale. In order to verify the robustness of the results, we rank all cities in terms of their economic scale, and then repeat the above regression analysis. The corresponding results are shown in Table 8.

Table 8: Impact of polycentric development on energy efficiency levels for large and small and medium-size cities (ranked by economic scale) in the period from 2005 to 2013

	Metropolis		Small and middle-size cities			All cities	
	Ranking<=3	Ranking<=4	Ranking>3	Ranking>4	Ranking>6	FE	RE
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
lnq	-0.0697	-0.0953	0.0426	0.0449	0.0732	-0.0081	-0.0016
	(0.0678)	(0.0586)	(0.0516)	(0.0571)	(0.0622)	(0.0409)	(0.0212)
Controlled variable	YES	YES	YES	YES	YES	YES	YES
Year effect	YES	YES	YES	YES	YES	YES	YES
Regional effect	YES	YES	YES	YES	YES	YES	YES
R^2	0.0038	0.0000	0.0083	0.0112	0.0061	0.0005	0.0180
Amount of observations	621	828	1845	1638	1224	2466	2466

***p<0.01, **p<0.05, * p<0.10. The standard deviation is the same in parentheses.

"Ranking<=3" indicates the top three cities ranked according to urban economic scale; "Ranking<=4" is the top four cities ranked according to urban economic scale; "Ranking>3" shows cities ranked after the top three according to the urban economic scale; "Ranking>4" represents cities ranked after the top four according to the urban economic scale; and "Ranking>6" indicates cities ranked after the top six according to the urban economic scale.

Table 8 confirms that, regardless of using the models of FE or RE, the polycentric development leads to the energy efficiency decline for large cities, but stimulates the growth for small and medium size cities. Moreover, the results are the same, despite the cities are ranked by population size or economic scale. This further proves the results are robust and confirms the statement given in Section 4.6, i.e. the RGEE is narrowed because the polycentric development has a negative effect on the energy efficiency of large cities, but a positive effect on that of small and medium size cities.

5. Discussions and policy implications

5.1 Discussions of the empirical results

Figure 2 is developed to summarize the main empirical results of this study. As shown in the figure, our results suggest that, the polycentric development has a narrowing effect on the RGEE. According to the theoretical elaborations in section 2.2, this might be due to several reasons. First, polycentric urban development can extend the geographic space of a single large center city to reduce uneconomic agglomerations (Phelps and Ozawa, 2003; Jahansson and Quigley, 2004; Luo et al., 2010) and form dynamic externalities. Meanwhile, the sub-central cities can avoid the high costs of the central area and enjoy the benefits of an agglomeration economy (Anas et al., 1998; Li et al, 2014). Second, through the size borrowing effect, efficient factor allocation will tend to balance the spatial value and narrow regional gaps, including the RGEE (Sovacool, 2011). Third, regional urban polycentric evolution can effectively promote the specialized division of cooperation, and balance productivity layout to reduce the RGEE between adjacent cities and achieve overall improvement (Meijers, 2007; Meijers & Burger, 2010; Wei et al., 2016; Song & Zhou, 2017).

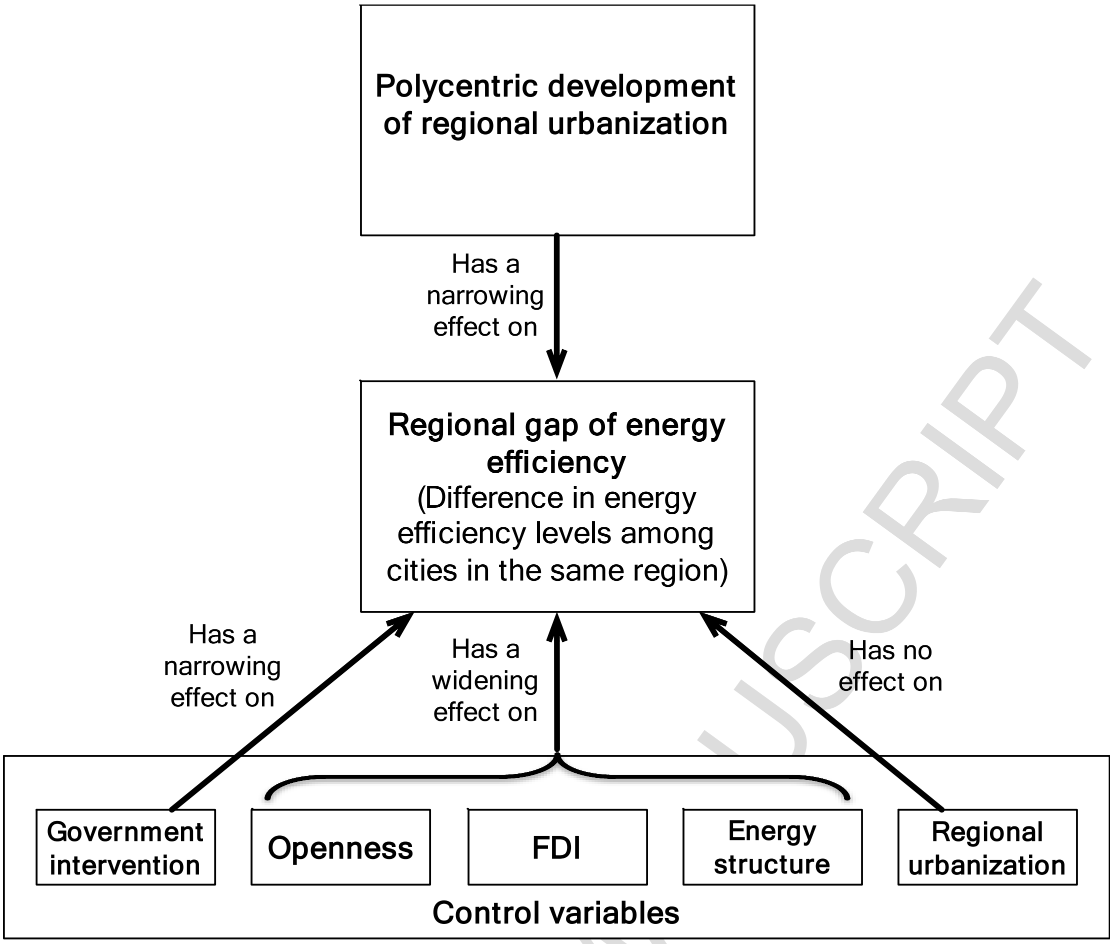


Figure 2: A summary of the empirical results of this study

Furthermore, the results of our additional analysis show, when ranking the cities in terms of population size and economic scale, the polycentric development has a negative effect on the energy efficiency of large cities, but a positive effect on that of small and medium size cities, which accordingly narrows the RGEE. This further suggests that, for large cities in China, polycentric development itself implies a more negative "resource competition" effect than a positive "catalytic coupling" effect (Mulíček & Malý, 2018). The former refers to the fact that all cities in polycentric networks are very close to each other and have limited resources, so they may face competition for resources among them. In this case, if large cities have not yet reached the optimal scale of agglomeration, they might have to face so called "agglomeration thinning" emphasized in the new economic geography, which has a negative impact on their energy efficiency. The latter emphasizes that the coupling of large and small and medium-size cities in urban systems in a region forms an orderly structure with a complementary function and symbiotic development. In the process of self-evolution, these cities form a symbiotic, coordinated, and orderly evolution system structure, and benefit from mutual support, mutual enhancement, mutual complementation, industrial association, and a coordinated development pattern. However, this structure also exhibits a more positive "agglomeration spillover" effect than a negative "price competition" effect on small and medium-size cities (Liu et al., 2017). The price competition effect refers to the fact that small and medium-size cities that are very close to large cities within the network may face price competition between them, which in turn leads to the "gathering shadow" emphasized in the new economic geography (Davis and Henderson, 2003). The agglomeration spillover effect emphasizes positive "network externality", which brings positive knowledge spillover from large cities to small and medium-size ones in the network (Liddle, 2013). Therefore, the effect of polycentric development on cities with different size can be the net effect of the two superimposed effects. In conclusion, we propose that the network externality effect of polycentric development can be stronger than the gathering shadow for small and medium-size cities and the negative "resource and price competition" effect for large cities.

Meanwhile, our results show the diverse impacts of our control variables on the RGEE. First, it is shown that OPEN has a significantly positive impact on RGEE, as suggested in Elliott et al. (2017) and Deichmann et al. (2018). Although it is surprising to see that the higher degree of openness leads to the higher RGEE, a possible explanation can still be given. To some extent, it is always difficult for small and medium-size cities to attract investment and cooperation, despite the province they belong to can be quite open. The investment and cooperation derived from the openness normally go to large cities in a province, rather than small ones. The large cities can certainly obtain more resource, knowledge, and experience to further improve their energy efficiency, which thereby leads to the increase of RGEE. Second, GOV is shown to have a significantly negative impact, as suggested in Zhao et al. (2015) and Li & Li (2017). It makes sense to see the higher degree of government intervention leads to the lower RGEE. Actually, in recent years, the Chinese government has introduced many policies to improve the economic and energy efficiency of developing areas/cities, which in turn leads to the decrease of RGEE. Third, FDI also has a significantly positive impact on RGEE, as suggested in Qi et al. (2009) and Chen et al. (2013). The explanation can be similar to the one for OPEN. FDI can introduce advanced technology and management experience to enterprises. Although all cities achieve certain results in attracting investment, it is easier for developed cities in a region to obtain high-quality FDI, which can bring in more efficient and cleaner technologies, thus enhancing the effective use of energy and leading to the increase of RGEE. Fourth, EST is also shown to have a significantly positive impact on RGEE, as suggested in Pan et al. (2013) and Zhang et al. (2015). The developing provinces in the West and North of China generally consume more coal in their energy consumption. In these provinces, cities are developed in a quite unbalance way. Several large and developed cities can perform much better in terms of energy efficiency than other cities in the same provinces, thus leading to the higher RGEE. Finally, URB is shown not to have a significant relationship with RGEE (Ma, 2015; Duro et al., 2017). This is beyond our expectation, but a possible explanation can be that, along with the growth of URB, the overall level of energy efficiency of all cities in a province gets improved, thus leading to the RGEE of this province unchanged.

5.2 Policy implications

The empirical results of this study have several important policy implications, as they not only reveal insights for policies that aim to reduce the RGEE, but also provide an empirical basis for future urban development strategies in the Chinese provincial context. A key finding of this study is that a Chinese province can follow the polycentric spatial development model to narrow its RGEE, but this approach might not be favorable for large cities in the province, as which needs them to sacrifice the improvement of their energy efficiency. In other words, it is not possible to achieve a "win-win situation" between improving the energy efficiency of all the cities in a province and narrowing the RGEE of that province, when following a polycentric spatial development model. Nonetheless, if aiming to narrow the RGEE of a province, a polycentric urban network should still be built on a provincial scale to avoid the excessive concentration of resources caused by a huge city. Therefore, two paths of urbanization might be followed by the policy makers. On the one hand, they can follow the polycentric spatial development model to firstly narrow the RGEE at the cost of decreasing energy efficiency of large cities, which might be improved together with the energy efficiency of small and medium-size cities in the future (Herrerias & Liu, 2013; Guo et al., 2015). On the other hand, they can choose to firstly strengthen the single large cities at the cost of widening the RGEE, which can be remedied by following the polycentric spatial development model at some point in the future. In doing so, a "win-win situation" can perhaps be achieved (Jones,1991; Ma, 2015; Sun & Wan, 2016). In fact, due to its advantages and the successful practice from ESDP, the polycentric development model of urbanization is currently regarded as an important means of adjusting regional development disparities, realizing sustainable development of metropolitan areas, and promoting the establishment of new urban-rural cooperative relations in China. Thus, China promotes polycentric urbanization and balanced agglomeration development, not only on the provincial level but also on the country level, by implementing special regional development policies, such as "the strategy of developing the west" and "revitalizing the northeast and central in China" (Li et al., 2015). In fact, since 2015, the State Council of China has approved nine national-level urban agglomerations, namely the middle reaches of the Yangtze River urban agglomeration, the Great Wall urban agglomeration, Chengdu-Chongqing urban agglomeration, the Yangtze River Delta urban agglomeration, the Central Plain urban agglomeration, Beibuwan urban agglomeration, Guanzhong Plain urban agglomeration, Hubao-Eryu urban agglomeration, and

Lanxi urban agglomeration (Gao et al., 2017; Jia et al., 2018; Kang et al., 2018; Liu et al., 2018). Moreover, on November 18, 2018, the Central government of China issued "Opinions of the State Council of the Central Committee of the Communist Party of China on the Establishment of a New Mechanism for More Effective Regional Coordination Development". It is clearly pointed out in the document that promoted by the urban agglomerations of seven city groups[3], the major regional strategies of the country are to establish a new model of urban agglomeration development led by central cities and regional development driven by urban agglomeration and to promote the integration and interactive development of regional plates.

6. Conclusions

This study discusses the impact of the polycentric development on the regional gap of energy efficiency, i.e. RGEE, in the Chinese provincial context, employing a novel method using DSMP/OLS nighttime lighting data to measure the spatial structure of provinces and SFA to evaluate the total-factor energy efficiency. According to our results, the polycentric development has a narrowing effect on the RGEE, reducing it by approximately 0.00367–0.00787 for every 10 percentage increase in the polycentric development index at a statistically significant level of 1%. Of the five control variables, OPEN, FDI, and EST are shown to have significant positive impacts; GOV has a significant negative impact; and URB has no significant impact on RGEE, which means the more government intervention can narrow the RGEE of a province, but being more open, having more FDI, and using more coal can widen the RGEE of that province. Furthermore, our empirical analysis shows that the polycentric development has a negative effect on the energy efficiency of large cities, but a positive effect on that of small and medium size cities, which accordingly narrows the RGEE. In order to better understand these empirical results, some potential explanations are provided in this study. Finally, some policy implications are also suggested based on these findings.

This study addresses the impact of a polycentric spatial development on the RGEE in detail, but it still has several important limitations. First, this study has merely discussed the relationship between the degree of polycentric development of a province and the RGEE. Nevertheless, the spatial scale of the study can be extended to urban agglomerations on the national level. In this new context, further analysis will be required to test whether our conclusions remain valid. Second, although this paper has proposed feasible ways to measure polycentric development and RGEE,

[3] Beijing, Tianjin, and Hebei; the Yangtze River Delta; Guangdong, Hong Kong and Macao; Chengdu and Chongqing; the middle reaches of the Yangtze River; the middle China; and the Central Plain Integrate development.

more innovative measurements might still be needed in order to better reflect the two variables. Third, this paper has described the robustness test in detail, but only involving a conventional lag choice and an alternative variable. In future, other tool variables should be analyzed in depth. Finally, some potential explanations have been given in this paper for the empirical findings, which however need to be further verified.

References

Alcantara, V., Duro, J.A., 2004. Inequality of energy intensities across OECD countries: A note. Energy Policy 32, 1257–1260. https://doi.org/10.1016/S0301-4215(03)00095-8

Al-mulali, U., Fereidouni, H.G., Lee, J.Y.M., Sab, C.N.B.C., 2013. Exploring the relationship between urbanization, energy consumption, and CO2 emission in MENA countries. Renew. Sustain. Energy Rev. 23, 107–112. https://doi.org/10.1016/j.rser.2013.02.041

Alonso, W., 1973. Urban Zero Population Growth. Daedalus 102, 191–206.

Anas, A., Arnott, R., Small, K.A., 1998. Urban Spatial Structure. J. Econ. Lit. 36, 1426–1464.

Ang, B.W., Choi, K.-H., 1997. Decomposition of Aggregate Energy and Gas Emission Intensities for Industry: A Refined Divisia Index Method. Energy J. 18. https://doi.org/10.5547/ISSN0195-6574-EJ-Vol18-No3-3

Au, C.-C., Henderson, J.V., 2006. Are Chinese Cities Too Small? Rev. Econ. Stud. 73, 549–576. https://doi.org/10.1111/j.1467-937X.2006.00387.x

Backlund, S., Thollander, P., Palm, J., Ottosson, M., 2012. Extending the energy efficiency gap. Energy Policy 51, 392–396. https://doi.org/10.1016/j.enpol.2012.08.042

Besagni, G., Borgarello, M., 2018. The determinants of residential energy expenditure in Italy. Energy 165, 369–386. https://doi.org/10.1016/j.energy.2018.09.108

Bilgili, F., Koçak, E., Bulut, Ü., Kuloğlu, A., 2017. The impact of urbanization on energy intensity: Panel data evidence considering cross-sectional dependence and heterogeneity. Energy 133, 242–256. https://doi.org/10.1016/j.energy.2017.05.121

Bo, L.I., Zhang, W.Z., Jian-Hui, Y.U., 2016. A Study on Total Factor Energy Efficiency and Its Difference in Resource-based Cities in China with Consideration of Environmental Constraints. J. Nat. Resour.

Brülhart, M., Sbergami, F., 2009. Agglomeration and growth: Cross-country evidence. J. Urban Econ. 65, 48–63. https://doi.org/10.1016/j.jue.2008.08.003

Burger, M.J., van der Knaap, B., Wall, R.S., 2014. Polycentricity and the Multiplexity of Urban Networks. Eur. Plan. Stud. 22, 816–840. https://doi.org/10.1080/09654313.2013.771619

Chang, G.H., Brada, J.C., 2006. The paradox of China's growing under-urbanization. Econ. Syst. 30, 24–40. https://doi.org/10.1016/j.ecosys.2005.07.002

Chen, C.-L., 2012. Reshaping Chinese space-economy through high-speed trains: opportunities and challenges. J. Transp. Geogr. 22, 312–316. https://doi.org/10.1016/j.jtrangeo.2012.01.028

Chen, L. 2017, Statistical study on the effect of Urban scale on energy efficiency. Zhejiang Industrial and Commercial University.

Chen, Q. 2017. Advanced econometrics and application of Stata. Higher Education Press, Beijing.

Chen, X., Qin, Q., Wei, Y.-M., 2016. Energy productivity and Chinese local officials' promotions: Evidence from provincial governors. Energy Policy 95, 103–112. https://doi.org/10.1016/j.enpol.2016.04.041

Chen, X.H., 2013. Spatial Conditional Β-convergence Analysis of Society-wide Energy Efficiency Based on Technological Diffusion. China Popul. Resour. Environ.

Chen, Y., Sun, B.D., 2017. Is there a "gathering shadow" in Beijing, Tianjin and Hebei? -- regional economic impact of big cities. Geogr. Research, 36(10): 1936-1946.

Cheng, K.M., 2011. The theoretical mechanism and empirical analysis of urban compactness affect on the energy consumption. Econ. Geogr., 7, 1107-1112.
Cheng, K.M., 2016. Urbanization and Energy Consumption: A Literature Review. Finance and Trade Research, 1, 36-44.
Davis, J.C., Henderson, J.V., 2003. Evidence on the political economy of the urbanization process. J. Urban Econ. 53, 98–125. https://doi.org/10.1016/S0094-1190(02)00504-1
Deichmann, U., Reuter, A., Vollmer, S., Zhang, F., 2018. Relationship between Energy Intensity and Economic Growth: New Evidence from a Multi-Country Multi-Sector Data Set. Policy Res. Work. Pap.
Donaldson, D., Storeygard, A., 2016. The View from Above: Applications of Satellite Data in Economics. J. Econ. Perspect. 30, 171–198. https://doi.org/10.1257/jep.30.4.171
Duranton, G., Puga, D., 2001. Nursery Cities: Urban Diversity, Process Innovation, and the Life Cycle of Products. Am. Econ. Rev. 91, 1454–1477. https://doi.org/10.1257/aer.91.5.1454
Duro, J.A., 2015. The international distribution of energy intensities: Some synthetic results. Energy Policy 83, 257–266. https://doi.org/10.1016/j.enpol.2015.03.022
Duro, J.A., Padilla, E., 2011. Inequality across countries in energy intensities: An analysis of the role of energy transformation and final energy consumption. Energy Econ. 33, 474–479. https://doi.org/10.1016/j.eneco.2010.12.008
Duro, J.A., Teixidó-Figueras, J., Padilla, E., 2017. The Causal Factors of International Inequality in CO 2 Emissions Per Capita: A Regression-Based Inequality Decomposition Analysis. Environ. Resour. Econ. 67, 683–700. https://doi.org/10.1007/s10640-015-9994-x
Dütschke, E., Hirzel, S., Idrissova, F., Mai, M., Mielicke, U., Nabitz, L., 2018. Energy efficiency networks—what are the processes that make them work? Energy Effic. 11, 1177–1192. https://doi.org/10.1007/s12053-017-9606-4
Elliott, R.J.R., Sun, P., Zhu, T., 2017. The direct and indirect effect of urbanization on energy intensity: A province-level study for China. Energy 123, 677–692. https://doi.org/10.1016/j.energy.2017.01.143
Ezcurra, R., 2007. Distribution dynamics of energy intensities: A cross-country analysis. Energy Policy 35, 5254–5259. https://doi.org/10.1016/j.enpol.2007.05.006
Farrell, M.J., 1957. The Measurement of Productive Efficiency. J. R. Stat. Soc. Ser. A 120, 253. https://doi.org/10.2307/2343100
Gao, X., Xu, Z., Niu, F., Long, Y., 2017. An evaluation of China's urban agglomeration development from the spatial perspective. Spat. Stat. 21, 475–491. https://doi.org/10.1016/j.spasta.2017.02.008

Garcia-López, M.-À., Muñiz, I., 2012. Urban spatial structure, agglomeration economies, and economic growth in Barcelona: An intra-metropolitan perspective. Pap. Reg. Sci. no-no. https://doi.org/10.1111/j.1435-5957.2011.00409.x
Giuliano, G., Redfearn, C., Agarwal, A., Li, C., Zhuang, D., 2016. Employment concentrations in Los Angeles, 1980-2000. Environ. Plan. A 15, 47–70. https://doi.org/10.1068/a393
Gollin, D., Jedwab, R., Vollrath, D., 2016. Urbanization with and without industrialization. J. Econ. Growth 21, 35–70. https://doi.org/10.1007/s10887-015-9121-4
Griffin, J.M., Gregory, P.R., 1976. An Intercountry Translog Model of Energy Substitution Responses. Am. Econ. Rev. 66, 845–857.
Guo, X., Sheng, P., He, Y., 2017. The Impact of Urbanization on Energy Consumption and Efficiency. Energy & Environ., 28.
Guo, W., Sun, T., Zhou, P., 2015. Evaluation of China Regional Total Factor Energy Efficiency and Its Spatial Convergence——Based on the Improved Undesirable SBM Model. Syst. Eng.
Han, F., Feng, P., Yang, L.G., 2014. Spatial Agglomeration Effects of China's Cities and Industrial Energy Efficiency. China Popul. Resour. Environ.

Hanson, G.H., 1996. Agglomeration, Dispersion, and the Pioneer Firm. J. Urban Econ. 39, 255–281. https://doi.org/10.1006/juec.1996.0014

Henderson, V., 2003. The Urbanization Process and Economic Growth: The So-What Question. J. Econ. Growth 8, 47–71.

Herrerias, M.J., Liu, G., 2013. Electricity intensity across Chinese provinces: New evidence on convergence and threshold effects. Energy Econ. 36, 268–276. https://doi.org/10.1016/j.eneco.2012.08.026

Honma, S., Hu, J.-L., 2014. A panel data parametric frontier technique for measuring total-factor energy efficiency: An application to Japanese regions. Energy 78, 732–739. https://doi.org/10.1016/j.energy.2014.10.066

Huang, Z.M., 2005. Self-organizing process analysis of multi-center urban space in China--Krugman model and urban evolution example in quanzhou region. Econo. Research J., 1, 85-94.

Jia, P., Li, K., Shao, S., 2018. Choice of technological change for China’s low-carbon development: Evidence from three urban agglomerations. J. Environ. Manage. 206, 1308–1319. https://doi.org/10.1016/j.jenvman.2017.08.052

Jiang, X., Duan, Y., Green, C., 2017. Regional disparity in energy intensity of China and the role of industrial and export structure. Resour. Conserv. Recycl. 120, 209–218. https://doi.org/10.1016/j.resconrec.2016.12.013

Johansson, B., Quigley, J.M., 2004. Agglomeration and networks in spatial economies. pp. 165–176. https://doi.org/10.1007/978-3-662-07223-3_7

Jones, D.W., 1991. How urbanization affects energy-use in developing countries. Energy Policy 19, 621–630. https://doi.org/10.1016/0301-4215(91)90094-5

Kamarajugedda, S.A., Mandapaka, P. V, Lo, E.Y.., 2017. Assessing urban growth dynamics of major Southeast Asian cities using night-time light data. Int. J. Remote Sens. 38, 6073–6093. https://doi.org/10.1080/01431161.2017.1346846

Kang, Z.-Y., Li, K., Qu, J., 2018. The path of technological progress for China’s low-carbon development: Evidence from three urban agglomerations. J. Clean. Prod. 178, 644–654. https://doi.org/10.1016/j.jclepro.2018.01.027

Kim, J.-U., 2015. A Bumpy Road to Cities: Analysis of the Obstacles and Limits of China’s New Urbanization. Pacific Focus 30, 372–388. https://doi.org/10.1111/pafo.12057

Kontuly, T., Dearden, B., 2003. Testing the temporal characterisation of the differential urbanisation model in western Germany, 1939-2010. Tijdschr. voor Econ. en Soc. Geogr. 94, 64–74. https://doi.org/10.1111/1467-9663.00237

Kuppusamy, T., Gandhi, B., 2010. Study on the Functional Polycentricity of Yangtze River Delta. Urban Plan. Int.

Li, J., Lin, B., 2017. Does energy and CO 2 emissions performance of China benefit from regional integration? Energy Policy 101, 366–378. https://doi.org/10.1016/j.enpol.2016.10.036

Li, J.M., Zhang, W.Z., Sun, T.S., 2014. Characteristics of clustering and economic performance of urban agglomerations in China. Acta Geogr. Sinica, 4, 474-484.

Li, M.Y., Xie, J.G., Zhang, E.Z., 2014. An analysis on the convergace of regional energy efficiency diffirence in china-Based on the Panal data. Econ. Science, 1, 23-38.

Li, Z., Li, G.P., 2010. Characteristics and influence factors of Urban Energy efficiency difference in China. Economic Theory and Business Management, 7, 17-23.

Li, Z., Lian, Y., Li P., Guo, J., 2015. Circling-Layering Economy,Temporal and Spatial Differences and Energy Intensity-Evidence from Urban Agglomerations. Urban Dev. Stud.

Liao, H., Fan, Y., Wei, Y.M., 2007. What induced China’s energy intensity to fluctuate: 1997–2006? Energy Policy 35, 4640–4649. https://doi.org/10.1016/j.enpol.2007.03.028

Liddle, B., 2013. The Energy, Economic Growth, Urbanization Nexus Across Development: Evidence from Heterogeneous Panel Estimates Robust to Cross-Sectional Dependence. Energy J. 34. https://doi.org/10.5547/01956574.34.2.8

Liddle, B., 2012. OECD energy intensity. Energy Effic. 5, 583–597. https://doi.org/10.1007/s12053-012-9148-8
Liddle, B., 2010. Revisiting world energy intensity convergence for regional differences. Appl. Energy 87, 3218–3225. https://doi.org/10.1016/j.apenergy.2010.03.030
Liu, B., Tian, C., Li, Y., Song, H., Ma, Z., 2018. Research on the effects of urbanization on carbon emissions efficiency of urban agglomerations in China. J. Clean. Prod. 197, 1374–1381. https://doi.org/10.1016/j.jclepro.2018.06.295
Liu, J.H., Shao, S., Jiang, X., 2015. The impact of urbanization on energy consumption: how far we are from the world---a comparative study based on domestic and international data. J. Finance and Econ., 2, 111-122.
Liu, L.T, Shen, L., 2010. Research on Spatial-Temporal Distribution Dynamic Evolution of Regional Energy Efficiency Disparity and influence factors in China. J. Natural Resour., 2512, 2142-2153.
Liu, X.Y., Li, S.L., Chen, Z.Y., 2017. Polycentric spatial development model and regional income disparity. China Industrial Econ., 10, 25-43.
Liu, X.Y., Li, S.L., Qin, M., 2017. Urban Spatial structure and Regional Economic efficiency: a discussion on the Mode selection of Chinaundefineds urbanization Development path. Managing World, 1, 51-64.
Liu, Y., Xie, Y., 2013. Asymmetric adjustment of the dynamic relationship between energy intensity and urbanization in China. Energy Econ. 36, 43–54. https://doi.org/10.1016/j.eneco.2012.12.003
Luo, Z.D., He, H.M., Geng, L., 2011. Analysis of the Polycentric Structure of Yangtze River Delta Based on Passengers Traffic Flow. Urban Planning Forum, 2,16-23.
Ma, B., 2015. Does urbanization affect energy intensities across provinces in China? Long-run elasticities estimation using dynamic panels with heterogeneous slopes. Energy Econ. 49, 390–401. https://doi.org/10.1016/j.eneco.2015.03.012
Ma, C., Stern, D.I., 2008. China's changing energy intensity trend: A decomposition analysis. Energy Econ. 30, 1037–1053. https://doi.org/10.1016/j.eneco.2007.05.005
Ma, T., Zhou, C., Pei, T., Haynie, S., Fan, J., 2012. Quantitative estimation of urbanization dynamics using time series of DMSP/OLS nighttime light data: A comparative case study from China's cities. Remote Sens. Environ. 124, 99–107. https://doi.org/10.1016/j.rse.2012.04.018
Meijers, E., 2007. Synergy in Polycentric Urban Regions. https://doi.org/10.1017/CBO9781107415324.004
Meijers, E.J., Burger, M.J., 2010. Spatial Structure and Productivity in US Metropolitan Areas. Environ. Plan. A 42, 1383–1402. https://doi.org/10.1068/a42151
Meng, M., Payne, J.E., Lee, J., 2013. Convergence in per capita energy use among OECD countries. Energy Econ. 36, 536–545. https://doi.org/10.1016/j.eneco.2012.11.002
Mishra, V., Smyth, R., 2014. Convergence in energy consumption per capita among ASEAN countries. Energy Policy 73, 180–185. https://doi.org/10.1016/j.enpol.2014.06.006
Mohammadi, H., Ram, R., 2017. Convergence in energy consumption per capita across the US states, 1970–2013: An exploration through selected parametric and non-parametric methods, Energy Economics. Elsevier B.V. https://doi.org/10.1016/j.eneco.2016.07.002
Mulíček, O., Malý, J., 2018. Moving towards more cohesive and polycentric spatial patterns? Evidence from the Czech Republic Mapping everydayness: representation of routine spaces View project. Pap. Reg. Sci. 1–18. https://doi.org/10.1111/pirs.12383
Pan, H., Zhang, H., Zhang, X., 2013. China's provincial industrial energy efficiency and its determinants. Math. Comput. Model. 58, 1032–1039. https://doi.org/10.1016/j.mcm.2012.09.006
Pan, X., Liu, Q., Zhang, W., Economics, S.O., 2014. Analysis of Energy Efficiency Convergence of China from the Perspective of Spatial Effect and Industry Transfer. Manage. Rev.
Phelps, N.A., Fallon, R.J., Williams, C.L., 2001. Small Firms, Borrowed Size and the Urban - Rural Shift. Reg. Stud. 35, 613–624. https://doi.org/10.1080/00343400120075885

Phelps, N.A., Ozawa, T., 2003. Contrasts in agglomeration: Proto-industrial, industrial and post-industrial forms compared. Prog. Hum. Geogr. 27, 583–604. https://doi.org/10.1191/0309132503ph449oa

Proskuryakova, L., Kovalev, A., 2015. Measuring energy efficiency: Is energy intensity a good evidence base? Appl. Energy 138, 450–459. https://doi.org/10.1016/j.apenergy.2014.10.060

Qi, S., Bo, Y., Li, K., 2009. International Comparative Analysis of the Convergence and Economic Mechanism of China's Economic Growth and Energy Intensity. Econ. Res. J.

Qi, S., Luo, W., 2007. Regional Economic Growth and Differences of Energy Intensity in China. Econ. Res. J.

Qin, X., Wei, Y., Chen, W., Duan, X., 2013. Population expansion and polycentric development of Nanjing city in a period of hyper-growth. Geogr. Res. 32, 711–719.

Rafiq, S., Salim, R., Nielsen, I., 2016. Urbanization, openness, emissions, and energy intensity: A study of increasingly urbanized emerging economies. Energy Econ. 56, 20–28. https://doi.org/10.1016/j.eneco.2016.02.007

Sadorsky, P., 2013. Do urbanization and industrialization affect energy intensity in developing countries? Energy Econ. 37, 52–59. https://doi.org/10.1016/j.eneco.2013.01.009

Shahbaz, M., Lean, H.H., 2012. Does financial development increase energy consumption? The role of industrialization and urbanization in Tunisia. Energy Policy 40, 473–479. https://doi.org/10.1016/j.enpol.2011.10.050

Shan, H.J., 2008. Reestimating the capital stock of China: 1952-2006. J Quant. Tech. Econ., 10,17-31.

Shi, B., Shen, K.R., 2013. Government intervention, economic agglomeration and energy efficiency. Management World,10, 6-18.

Simon-Elorz, K., Arcelus, F.J., Melgarejo, Z., 2011. A three-stage DEA-SFA efficiency analysis of labour-owned and mercantile firms. J. Ind. Manag. Optim. 7, 573–592. https://doi.org/10.3934/jimo.2011.7.573

Song, W., Zhou, Y., 2017. Biased technological Progress, element substitution and Twisted urbanization: an econometric Analysis of Spatial economy based on Provincial Panel data of China. Inquiry into Econ. Issues, 7, 124-134.

Sovacool, B.K., 2011. An international comparison of four polycentric approaches to climate and energy governance. Energy Policy 39, 3832–3844. https://doi.org/10.1016/j.enpol.2011.04.014

Su, S., Liu, Z., Xu, Y., Li, J., Pi, J., Weng, M., 2017. China's megaregion policy: Performance evaluation framework, empirical findings and implications for spatial polycentric governance. Land use policy 63, 1–19. https://doi.org/10.1016/j.landusepol.2017.01.014

Sun, B., Song, D., 2017. Progress and Implications for Polycentric Spatial Structure's Effect on Economic Performance. Sci. Geogr. Sin.

Sun, B., Wan, L., 2016. City Size Distribution and Economic Performance:Evidence from City-Regions in China. Sci. Geogr. Sin.

Sun, J.W., 2002. The decrease in the difference of energy intensities between OECD countries from 1971 to 1998. Energy Policy 30, 631–635. https://doi.org/10.1016/S0301-4215(02)00026-5

Sun, Y., Zhang, X., Ren, G., Zwiers, F.W., Hu, T., 2016. Contribution of urbanization to warming in China. Nat. Clim. Chang. 6, 706–709. https://doi.org/10.1038/nclimate2956

Swyngedouw, E., Moulaert, F., Rodriguez, A., 2002. Neoliberal Urbanization in Europe: Large-Scale Urban Development Projects and the New Urban Policy. Antipode 34, 542–577. https://doi.org/10.1111/1467-8330.00254

Tan, M., Li, X., Li, S., Xin, L., Wang, X., Li, Q., Li, W., Li, Y., Xiang, W., 2018. Modeling population density based on nighttime light images and land use data in China. Appl. Geogr. 90, 239–247. https://doi.org/10.1016/j.apgeog.2017.12.012

Tao, C.Q., Wang, Z.P., 2011. Advances and prospects of stochastic frontier methods. J. Quantitative Tech. Econ., 11,148-160.

Thoyre, A., 2015. Energy efficiency as a resource in state portfolio standards: Lessons for more expansive policies. Energy Policy 86, 625–634. https://doi.org/10.1016/j.enpol.2015.08.015

Wan, J., Baylis, K., Mulder, P., 2015. Trade-facilitated technology spillovers in energy productivity convergence processes across EU countries. Energy Econ. 48, 253–264. https://doi.org/10.1016/j.eneco.2014.12.014

Wang, F., Dong, S., Mao, Q., 2013. Evolution of China's industrial structure and regional disparities in energy consumption intensity. Prog. Geogr. 32, 522–531.

Wang, K., 2012. The Measurement and Convergence of China's Total-factor Energy Efficiency under the Environmental Constraints. Chinese J. Manag.

Wang, Q., Fan, J., Shidai, W.U., 2014. Spatial-temporal variation of regional energy efficiency and its causes in China, 1990-2009. Geogr. Res. 33, 43–56.

Wang, S., Li, G., Fang, C., 2018. Urbanization, economic growth, energy consumption, and CO2 emissions: Empirical evidence from countries with different income levels. Renew. Sustain. Energy Rev. 81, 2144–2159. https://doi.org/10.1016/j.rser.2017.06.025

Wang, W.G., Fan, D., 2012. Influential Factors and Convergence of Total Factor Energy Efficiency in China Based on the Malmqulist-Luenberger Index. Resour. Sci. 34, 1816–1824.

Wang, Z.H., Feng, C., Hao, Y., 2013. Trend and Convergence Analysis of Total Factor Energy efficiency in typical regions of China: a case study of eight Economic regions. J Beijing University of Tech., 5, 1-9.

Wei, S.H., Chen, Y.K., 2016. Urban sprawl, multi-center agglomeration and productivity. China Ind. Econ.

Wiese, C., Larsen, A., Pade, L.-L., 2018. Interaction effects of energy efficiency policies: a review. Energy Effic. 11, 2137–2156. https://doi.org/10.1007/s12053-018-9659-z

Williamson, J.G., 1965. Regional Inequality and the Process of National Development: A Description of the Patterns. Econ. Dev. Cult. Change 13, 1–84. https://doi.org/10.1086/450136

Wu, J., Wu, Y., Se Cheong, T., Yu, Y., 2018. Distribution dynamics of energy intensity in Chinese cities. Appl. Energy 211, 875–889. https://doi.org/10.1016/j.apenergy.2017.10.097

Wu, Y., 2012. Energy intensity and its determinants in China's regional economies. Energy Policy 41, 703–711. https://doi.org/10.1016/j.enpol.2011.11.034

Xiaoyu, M.A., Qiangyi, L.I., Han, Y., 2015. Energy Intensity Convergence Theory and Empirical Analysis in China. Sci. Technol. Manag. Res.

Xu, D., 2016. Analysis of Current Interregional Industry Transfer and Its Features in China Based on Three Dimensions. Chinese J. Urban Environ. Stud. 04, 1650021. https://doi.org/10.1142/S2345748116500214

Yan, H., 2015. Provincial energy intensity in China: The role of urbanization. Energy Policy 86, 635–650. https://doi.org/10.1016/j.enpol.2015.08.010

Yan, H., Sun, B.D., 2015. Energy consumption performance of multi-Center urban spatial structure: an empirical study based on cities above prefecture-level in China. Urban Development Studies, 12, 13-19.

Yuan, X.L., Li, Y., 2015.Whether the urban agglomeration can improve its total-factor energy efficiency-A case study of the top ten urban agglomerations in China. Science Tech. Progress and Policy, 20, 8-43.

Zhang, H., Lahr, M.L., 2014. Can the carbonizing dragon be domesticated? insights from a decomposition of energy consumption and intensity in China, 1987–2007. Econ. Syst. Res. 26, 119–140. https://doi.org/10.1080/09535314.2014.880663

Zhang, L., Yue, W.Z., Liu, Y., 2017.Study on multi-dimensional recognition of multi-center urban spatial structure: a case study of Hangzhou. Econ.Geogr., 6, 67-75.

Zhang, W., Pan, X., Yan, Y., Pan, X., 2017. Convergence analysis of regional energy efficiency in china based on large-dimensional panel data model. J. Clean. Prod. 142, 801–808. https://doi.org/10.1016/j.jclepro.2016.09.096

Zhang, W.H., Wang, W., Hu, G., 2003. Urban development strategy based on low traffic energy consumption. J.Highway Trans.Research Dev., 1, 80-84.

Zhang, Y.J., Liu, Y.W., Zong-Yi, H.U., 2015. The Analysis On Convergent Regional Differences and Influential Factors of Energy Consumption Intensity. Mod. Financ. Econ. Tianjin Univ. Financ. Econ.
Zhang, Z.H., 2015. Evolution of Regional Energy efficiency in China and its influencing factors. Research on quantity econ.Tech. econ., 8, 73-88.
Zhao, J.L, Li, G., Su, Y., Liu, J.G., 2013.Regional difference and convergence analysis of energy efficiency in China: an empirical study based on stochastic frontier analysis and panel unit root. Chinese J. of management science, 2, 175-184.
Zhao, M., Cheng, W., Zhou, C., Li, M., Huang, K., Wang, N., 2018. Assessing Spatiotemporal Characteristics of Urbanization Dynamics in Southeast Asia Using Time Series of DMSP/OLS Nighttime Light Data. Remote Sens. 10, 47. https://doi.org/10.3390/rs10010047
Zhao, N., Wang, X.R., Zhu, W.J., 2015. Research on Convergence of Regional Energy efficiency in China. Statistical Research, 3, 29-35.
Zhou, P., Ang, B.W., Zhou, D.Q., 2012. Measuring economy-wide energy efficiency performance: A parametric frontier approach. Appl. Energy, 90, 196–200. https://doi.org/10.1016/j.apenergy.2011.02.025
Zhou, Y., Ma, L.J.C., 2000. Economic restructing and suburbanization in China. Urban Geogr. 21, 205–236. https://doi.org/10.2747/0272-3638.21.3.205
Zhu, Y., Xia, Y., 2018. Industrial agglomeration and environmental pollution: Evidence from China under New Urbanization. Energy Environ. 0958305X1880278. https://doi.org/10.1177/0958305X18802784

Appendix: abbreviation and notation list

	Abbreviation and notation	Full term
1	REEG	Regional energy efficiency gap
2	DSMP/OLS	The Defense Meteorological Satellite Program's Operational Linescan System
3	SFA	Stochastic Frontier Approach
4	DEA	Data envelopment analysis
5	GDP	Gross Domestic Product
6	ESDP	European Spatial Development Perspective
7	C-D production function	Cobb-Douglas production function
8	CES functions	Constant elasticity of substitution functions
9	ML	Maximum likelihood method
10	CV	Coefficient of variation
11	DN	Digital Number
12	FDI	Foreign direct investment