



Energy consumption in China: Spatial effects of industrial concentration, localization, and diversity

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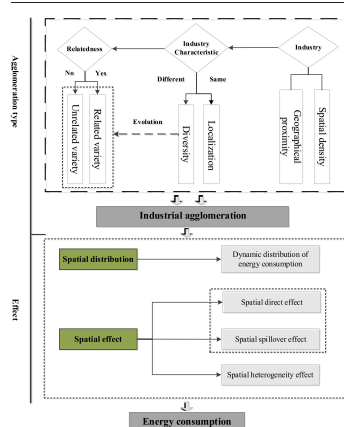
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HIGHLIGHTS

- Theoretical hypotheses are built to clarify the effects of different types of industrial agglomerations on energy consumption.
- Spatial Durbin model (SDM) is adopted to analyze the spatial effects with the panel data of China's 285 cities.
- Heterogeneous spatial effects of industrial agglomeration are explored across regional-scale and city-size.
- Different agglomeration types play different roles in explaining energy consumption directly and indirectly.
- Spatial spillover effects are heterogeneous across regions as well.

GRAPHICAL ABSTRACT



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ABSTRACT

This paper discusses the effects of industrial agglomeration on electrical energy consumption from a spatial perspective by highlighting multiple agglomeration types. It is argued that different types of industry agglomeration may exert differentiated effects on energy consumption and their possible spatial interactions. With city sector panel data of China's 285 prefecture-level cities for the period 2003–2013, we adopted the Spatial Durbin Model (SDM) with fixed effects to examine the spatial effects of industrial agglomeration types on energy consumption. The model found that all types of industrial agglomeration play significant and different roles in explaining overall local energy consumption. Second, geographical proximity, diversity, and related variety show the spatial spillover effects on surrounding areas. Third, the spatial energy effects of industrial agglomeration across regions are evidently heterogeneous. Diversity and one of its sub-forms-related variety maintains consumption-saving effects in regions with the initial or intermediate stage of an industry life cycle, while unrelated variety changes over different phases. The results suggest that policy-makers scientifically discriminate regional features and guide the agglomerated types of industries in order to balance economic growth with energy conservation.

1. Introduction

Energy crisis is a huge challenge for countries around all the world due to supply shortages and overuse of inefficient utilization of energy. How to

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promote energy conservation and efficiency has been an urgent and hotly debated issue, no matter how important it is for policymakers, businesses, and researchers. As the bulk of literature reveals, the positive externalities of agglomeration on regional economic growth, firm growth, and innovation (Basile et al., 2017; Cainelli et al., 2014; Neffke et al., 2011; Renski, 2011), related scholars have started to concern the possible effects of agglomeration on energy consumption recently (Otsuka et al., 2014; Wang and Wang, 2019; Wu and Lin, 2021), but the analytical perspectives and approaches of which are various with inconsistent conclusions. As such, growing empirical cases are offered to uncover the uncertain link between energy consumption and industrial agglomeration.

Prior empirical studies on the link between industrial agglomeration and energy consumption are mainly based on two typical agglomeration types—localization and diversification—which are supposedly supported by the hypothesis of Marshall (1920) and Jacobs (1969). In addition, the other two initial types—spatial density and geographical proximity without interconnection between industries—are gradually being neglected (Ciccone and Hall, 1996). However, those above types are unable to explain the further evolution of the intertwined relationship between industrial activities. With the emergence of Evolutionary Economic Geography, Frenken et al. (2007) and Boschma and Lammarino (2010) set forth new insights by extending Jacobs's diversity to related variety and unrelated variety based on cognitive link between industries. However, so far, no related evidence has been provided on their link with energy consumption. Given that different types of agglomeration possibly have different effects on energy consumption, capturing and comparing the effects of multiple types of agglomeration contribute to comprehensively understanding their relationship.

Moreover, elements diffuse and flow between regional industries, with the decreased cost of transportation and communication (Van Soest et al., 2006). However, the spatial effects of industrial agglomeration on energy consumption are generally ignored. Thus, the estimates of the traditional ordinary least squares regression (OLS) without spatial variables are biased and inconsistent. The spatial econometric approach that allows for spatial interactions between industrial agglomeration and energy consumption contributes to avoiding estimation deviation caused by neglecting the spatial effect and getting a more accurate and reliable estimate (Yang et al., 2020). As such, the impact assessment of energy consumption from a spatial perspective should be highlighted.

Finally, the external effects of industrial agglomeration on energy consumption differ across regions and industries due to such factors as urban development level or city size (De Groot et al., 2016; Faggio et al., 2017). However, related studies have been conducted primarily on a large scale, such as in provincial regions, and few studies have analyzed the heterogeneous effect on a smaller scale, that is, the municipal/city level. It is difficult to determine the applicability of the effects across different regional scales (Wu et al., 2020; Wu and Lin, 2021). Therefore, the heterogeneous spatial effects of agglomeration across regions are necessary to be captured, to complement the empirical cases.

In the context of China, as an example, our paper aims to establish the spatial effects of industrial agglomerations of multiple types of energy consumption. As we know, energy utilized in industries mainly includes natural gas, liquefied petroleum gas, and electricity. Herein, considering

the increasing utilized proportion of industrial electricity consumption in industrial energy consumption, we used industrial electrical energy consumption to proxy energy consumption (Freire-González et al., 2017). With city sector panel data of China's 285 prefecture-level cities from 2003 to 2013, we used the Spatial Durbin Model (SDM) to examine the spatial effects of industrial agglomeration on energy consumption by highlighting different agglomeration types. Furthermore, we test the spatial heterogeneity effects of industrial agglomeration across regions.

The contributions of this paper for the existing literature are twofold. First, we systematically discuss the effects of industrial agglomeration based on its multiple types, by detangling diversity to related variety and unrelated variety and adding the initial agglomeration density and proximity, rather than concerning the role of general specialization and diversification on energy consumption. Second, based on this, this paper from a spatial perspective captures the spatial effects of industrial agglomeration on electricity consumption and also makes regression estimates more precise. Finally, we further investigate the heterogeneous spatial effects of the different agglomeration types on energy consumption for different region subdivisions.

The remainder of this paper is structured as follows. The next section presents a review of the literature and our conceptual framework. The data and methodology are introduced in Section 3. Section 4 introduces the pattern of industrial electricity consumption, and the empirical results are presented in Section 5. Section 6 concludes.

2. Literature review and conception frameworks

2.1. Types of industrial agglomeration

Scholars studying industrial agglomeration have examined its types ranging from external manifestation to, as research progressed, its complicated internal structures (see Fig. 1). Originally, when a number of industries gathered geographically, the geographical concentration pattern in space received attention, regardless of industrial characteristics, and spatial density was the superficial index used to measure industrial agglomeration (Desrochers, 2001; Duranton and Overman, 2005). Meanwhile, from a micro-geographic firm perspective, Duranton and Overman (2005) computed the geographical proximity to evaluate industrial agglomeration based on a firm's location. Therefore, the early manifestation of industrial clustering in physical space traditionally took the form of spatial density and geographical proximity.

Moreover, under the externality hypothesis of Marshall and Jacobs, industrial agglomeration at a regional level is divided into two prevalent types—namely, localization and diversity (Glaeser et al., 1992)—based on whether the agglomeration is that of a single industry (Marshall, 1920). Localization (or specialization) refers to the concentration situation of firms in the same industry (intra-industry), which derives from the specialization of an industrial structure (Marshall, 1920). Diversity is the agglomeration performance of a variety of economic factors in different industries (inter-industries), which originates from the diversity of industrial structures (Jacobs, 1969). However, the above types are far from sufficient to interpret the influence caused by agglomeration because the internal links between industries are neglected.

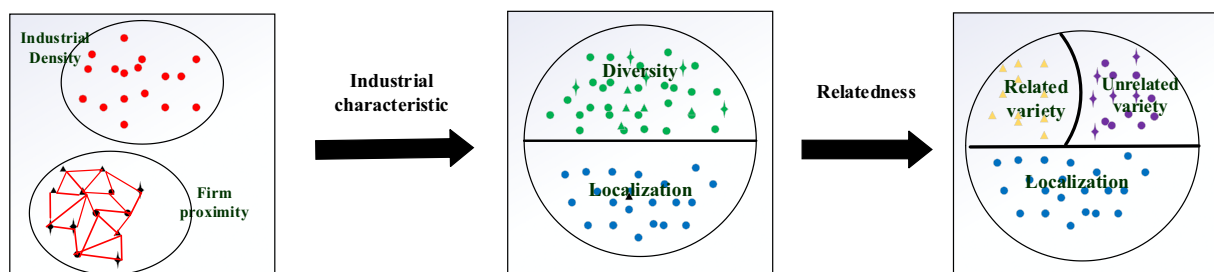


Fig. 1. The performance types of industrial agglomeration.

According to the increasing research on industrial agglomeration in Evolutionary Economic Geography, Frenken et al. (2007) and Boschma and Lammarino (2010) subdivided Jacobs's agglomeration externality diversity into a related variety and an unrelated variety, according to the shared or complementary competencies across industrial sectors. Related variety denotes the clustering of industries/sectors with strong technological links, while unrelated variety refers to the geographical concentration of industries/sectors that have weak or no technological and input–output links. So far, less attention has been paid to the energy effect of (un)related variety.

2.2. Impacts of industrial agglomeration on energy consumption

Energy consumption is regarded as the input factor of industries. Industrial agglomeration can improve the efficiency of energy resource allocation and utilization through knowledge spillovers, technological innovation, and resource sharing. Therefore, we consider the effect of industrial agglomeration on energy consumption based on multiple types of agglomeration.

Spatial density and proximity directly reflect the concentrated degree of industrial agglomeration, regardless of industrial characteristics. On the one hand, distance proximity and concentration of industries promote the spillover of knowledge and technology, improve productivity and energy-saving technology, and further lower the intensity and scale cost of energy consumption (Ciccone and Hall, 1996; Gertler, 1995; He et al., 2017), and vice versa (Gertler, 1995; Lin, 2016). On the other hand, industrial agglomeration accompanied by an increase in firms' scale increases energy consumption (Ellison and Edward, 1997).

Localization (i.e., the agglomeration of intra-industries) is conducive to optimizing resource allocation and achieving economies of scale through sharing and matching the specialized labor and intermediate inputs, thereby reducing energy utilization. While there may be a “rebound” effect of energy—namely an increase in energy demand in response to the decreased energy prices induced by economies of scale (Li and Lin, 2018)—it promotes a decrease in energy consumption and enhances energy efficiency via the sharing of knowledge and technology between similar industries from two paths (Boyd and Pang, 2000; Combes et al., 2012; Li and Lin, 2018). The improved production efficiency induced by knowledge spillovers can boost energy intensity (i.e., reduce energy input). Meanwhile, spillover of green and energy-saving technology and sharing energy-saving resources improve energy efficiency and structure through technological progress (Worrell et al., 2000). However, excessive agglomeration probably causes overcrowding and fierce competition for resources and knowledge across industries, which misallocates resources and hinders inter-industry exchanges and technology spillover. Thus, the over-crowded effect and knowledge protection lower productivity, and thus intensify energy consumption.

Diversity (inter-industrial agglomeration) facilitates the exchange of knowledge across sectional borders, cooperation across industries, and the sharing of infrastructure, and it attracts the inflow of skilled labor. Analogous to specialized agglomeration, diversity thus also exerts economies of scale and technological spillover to promote the technological innovation of production and energy-saving, and thus improves the efficiency of energy resource allocation (Audretsch and Feldman, 1998; Han et al., 2018b). However, diversified agglomeration may also increase energy consumption. Boschma (2005) indicated that there are many barriers to diffusion, such as input-sharing (including labor and infrastructure), and even knowledge and technology spillovers cross-industry when their cognitive distances increase. Furthermore, the effect of diversity on energy consumption may change from negative to positive throughout the stages of the cluster life cycle (Ingstrup and Damgaard, 2013). When the capacity of agglomeration across inter-industries reaches saturation point, the outdated technology and rigid structure lock the agglomeration into the formed path. In this case, the recession of diversified agglomeration inevitably reduces the efficient use of energy (Neffke et al., 2011; Xie and Yuan, 2016).

Regarding the related variety (i.e., industries with strong cognitive links), the intensively interactive learning enhances knowledge spillovers

and stimulates the technological innovation of production and energy utilization (Boschma and Frenken, 2011), further promoting energy efficiency and reducing energy consumption. Furthermore, the competition and cooperation resulting from the stronger link between firms are conducive to saving input costs and improving productivity, and finally lowering energy input. However, unrelated variety may also have a cognitive lock-in risk (Nooteboom, 2000) when the cognitive proximity is over the threshold value. For the unrelated variety of industrial agglomeration (i.e., industries with weak or no cognitive links agglomeration), the weak or absent cognitive links between sectors hinder technological innovation, because it is difficult to share mutual learning and even spill over knowledge and technology, which may promote energy efficiency (Neng et al., 2018).

Hypothesis 1. The above kinds of industrial agglomeration can exert significant effects on energy consumption, but the effects of which may be positive or negative.

2.3. Spatial spillover effects of industrial agglomeration and energy consumption

Thanks to element resources diffusing and flowing across space (Ciccone, 2002), spatial relation between industrial agglomeration and energy consumption may exist. For one thing, industrial agglomeration conducts spatial spillover effects, besides it acts on local energy consumption. Regions that are within proximity of each other, in terms of space or cognition, contribute to element spillovers/flow from industrial agglomeration externality. As such, industrial structure in the other regions may be upgraded through industry matching and resources flow like labors, information, and technology, improving energy-saving technology. Inversely, agglomeration shadows may occur between regions within proximity of each other. Regions with a high ratio of primacy may attract more elements, constraining the flow of resources and technological progress in other regions.

For one reason or another, energy consumption may generate negative or positive spatial dependence acting on the spread effect of environmental pollution between regions. On the one hand, energy conservation behavior in one region probably lessens the motivation to improve energy consumption in the surrounding areas, due to “free riders” who lower environmental standards. On the other hand, regions are in the situation in that they are pursuing economic growth and energy conservation at the same time, while regional governments may scramble for the double goals through competing for the investment or resources and imitating innovational technology. The competitive effect and the demonstration effect thus contribute to the positive spatial correlation of energy consumption across regions.

Therefore, the interaction between industrial agglomeration and energy consumption in an area can affect activities in the surrounding areas. Therefore, this study proposes:

Hypothesis 2. Industrial agglomeration and energy consumption can exhibit the spatial spillover effects for surrounding areas, but the positive or negative is uncertain.

3. Data source and measurements

3.1. Measuring industrial agglomeration and energy consumption

3.1.1. Spatial density and geographical proximity

3.1.1.1. Spatial density. We calculated the indicator of spatial density by all industrial density in city i as follows:

$$den_i = \frac{ind_i}{km_i} \quad (1)$$

where ind_i is the total industrial output and $area_i$ is the land area of city i . The average industrial density den_i refers to the proportion of the total industrial output in each square kilometer of city i .

3.1.1.2. Geographic proximity. As for geographic proximity of industries within a region, the distribution of firm points is a prioritized proxy for the clustering degree of industries at a micro-city level. Using the methodology of Duranton and Overman (2005), we calculated the coefficient of variation for the latitude and longitude of each firm point in city i as a proxy for the physical proximity of firms across all sectors as follows:

$$prox_i = -\ln(CV_{latitude-firm} \times CV_{longitude-firm}). \quad (2)$$

The greater the proximity, the more concentrated the distribution of firms within city i .

3.1.2. Regional localization (Mar) and diversity (Jacobs)

Following the measuring methodology of regional relative (rather than absolute) localization and diversity of Duranton and Puga (2000), we measured localization and diversity in a region based on the industrial output value, because the major components of localization and diversity are the specialization and diversity of industrial structures, respectively (Fujita and Thisse, 1996).

3.1.2.1. Localization. The relative localization index is expressed by dividing the share of each sector in local output value by its share in national output value, as follows:

$$rzi = \frac{\max_j (s_{ij}/s_j)}{s_j}. \quad (3)$$

3.1.2.2. Diversity. We set the deformation of the Herfindahl index to measure the diversification of regions, allowing optimal horizontal comparison between cities. This index is calculated by adding for each city, across all sectors, the absolute value of the difference between each sector's share in the value of local industrial output and its share in the value of national production. This leads to:

$$rdi = 1/\sum_j |s_{ij} - s_j| \quad (4)$$

where s_{ij} indicates the share of the total industrial output value industry j in city i , and s_j refers to the share of total industry j in national output value. The larger the rzi (rdi), the higher the level of localization (diversity).

3.1.3. Related variety and unrelated variety

The entropy indicator method of Frenken et al. (2007) was used to measure the related variety and the unrelated variety. We classified 37 two-digit industry sectors in China into four aggregated categories according to the input–output relationship across industries (Pan et al., 2012). In this case, the sectors within each large category are related, while the four large categories are unrelated. Hence, unrelated variety (uv) is the

entropy of the large category, while related variety (rv) is represented by the weighted sum of the entropies of the subsectors in each large category:

$$uv = \sum_{g=1}^4 p_g \log_2 \left(\frac{1}{p_g} \right), rv = \sum_{g=1}^4 p_g h_{gi}, \quad (5)$$

$$h_{gi} = \sum_{j \in g} \frac{p_{ji}}{p_g} \log_2 \left(\frac{1}{\frac{p_{ji}}{p_g}} \right) \quad (j = 1, \dots, 37; g = 1, 2, 3, 4.)$$

In Eq. (5), j is the 37 chosen sectors, g refers to the four industry categories, p_j denotes the share of sector j 's outputs in the total output, and p_g is the share of industry category g 's outputs in the total output, while h_{gi} is the entropies of variety of sector j in category g . Therefore, the larger the uv , the higher the noncorrelation degree of the industry agglomeration. The larger the rv , the higher the correlation degree of the agglomeration industry.

3.1.4. Energy consumption

In this paper, we use industrial electrical energy consumption to represent industrial energy consumption, because China's industries mainly consume electricity and less attention has been paid to it in previous research (Wang et al., 2010). We calculated industrial electricity consumption intensity as indicator,

$$energy_{i,t} = w_{i,t}/y_{i,t} \text{ (Unit : tWh/100 million yuan)}. \quad (6)$$

where $w_{i,t}$ refers to the total industrial electricity consumption in city i in year t , and $y_{i,t}$ is the total industrial output in city i in year t . Here, the logarithm of industrial electricity consumption intensity $lnenergy$ is used in our models.

In addition, we added the below control variables that influence energy consumption into our regression models to reduce the estimation errors of our results, according to the related literature and theoretical relations. The descriptive statistics of all variables are presented in Table 1.

3.2. Model specification

3.2.1. Basic econometric model

To explore the impacts of multiple types of agglomeration on energy consumption, we first constructed a general panel regression model, which eliminates endogenous problems between dependent variables and ignored related variables. Meanwhile, the logarithmic form of variables adopted contributes to eliminate heteroscedasticity. The equation is as follows:

$$lnenergy_{it} = \alpha_0 + \beta_1 aggl_{it} + \beta_2 pop_{it} + \beta_3 str_{it} + \beta_4 open_{it} + \beta_5 tec_{it} + \beta_6 er_{it} + \varepsilon_{it} \quad (7)$$

where α_0 is a constant, $\beta_1, \beta_2, \dots, \beta_6$ are the estimate coefficients of variables, and ε_{it} is an error term. i and t refer to the city and year, respectively. In our

Table 1
Variable definitions and summary statistics.

Variables	Definition	Measure	Obs.	Mean	Std. Dev	Min	Max
<i>lnenergy</i>	Energy intensity	Logarithm of industrial electricity consumption intensity	3135	9.207	1.204	2.011	14.19
<i>den</i>	Industrial spatial density	Relative industrial density	3135	11.13	2.635	1	16.82
<i>pro</i>	Concentration (proximity)	Concentration	3135	12.86	1.739	4.700	35.97
<i>rzi</i>	Specialization	Location quotient of the largest industry	3135	19.71	45.81	1.754	1028
<i>rdi</i>	Diversity	Deformation of the Herfindahl index of largest industry in the city	3135	1.088	0.292	0.528	3.349
<i>rv</i>	Related variety	Weighted sum of the entropies of the subsectors in each sector of 39 two-digit sectors	3135	1.570	0.616	0.0159	2.803
<i>uv</i>	Unrelated variety	Entropy across 4 large sectors	3135	1.439	0.350	0.0843	1.999
<i>pop</i>	Population size	Logarithm of population density	3135	9.348	1.406	3.700	13.78
<i>str</i>	Industrial structure	Proportion of the added value of the tertiary sector output in GDP	3135	35.71	8.386	8.580	85.34
<i>open</i>	Opening to the outside world	Actual use of FDI as a percentage of GDP	3135	0.351	0.406	0	4.540
<i>tec</i>	Technological level	Ratio of science and technology expenditure to fiscal expenditure	3135	1.135	1.197	0.00289	12.79
<i>er</i>	Environmental regulation	Logarithm of treatment rate of industrial SO ₂	3135	0.363	0.701	−35.06	0.998

models, the logarithm forms of industrial energy consumption intensity ($\ln energy$), population size pop , and environmental regulation er are used.

3.2.2. Spatial Durbin model

To account for the potential spatial interactions and obtain an accurate estimation, we further estimated the spatial econometric regressions to complement the limitations of the aforementioned basic models. Given the spatial Wald tests of the spatial lag model (SLM), spatial error model (SEM) and SDM for all the models show that the null hypothesis that spatial lag and spatial error do not exist at the same time cannot be rejected, the SDM is preferred to SLR and SEM in our empirical analysis. As is known, the SDM deals with the endogenous problems caused by explanatory variables other than time lag and space lag, and significantly reduces the bias of spatial autoregressive coefficients, and captures the data-generating process even when relevant spatially related variables are omitted from the model formulation as well (LeSage and Pace, 2009).

Thus, this paper chose the Spatial Durbin Model set as follows:

$$Y = \rho WY + \beta aggl + \alpha X + \nu W aggl + WX\theta + \varepsilon, \varepsilon = \lambda W\varepsilon \quad (8)$$

where Y is the independent variable, $aggl$ refers to industrial agglomeration variables, and X includes all control variables, W is the spatial weight of inverse-distance based on Euclidean distance, ρ implies the spatial spillover effects of local industrial agglomeration on the surrounding areas, and ε is the residual term.

3.3. Data source

The study area comprised China's 285 prefecture-level Chinese cities in the period 2003–13, because the output values of two-digit sectors at the city level have not been updated since 2013. The industrial data were extracted from the Annual Survey of Industrial Firms (ASIFs) published by the Chinese National Bureau of Statistics (NBS). We chose 39 two-digit sectors (SIC codes 06–46)—including mining, manufacturing, electricity, gas, and water production—that cover all state-owned and nonstate-owned industrial enterprises with sales revenues greater than five million

yuan. Data on the urban residential population used to divide the city size were obtained from the China Urban Construction Statistical Yearbook (2004–14). The other data at the city level were obtained from the China City Statistical Yearbook (2004–14).

4. Pattern of industrial consumption

4.1. Change in industrial electricity consumption

With the rapid urbanization and industrialization of Chinese cities, industrial electricity consumption underwent a fluctuating downtrend from 2397.91 kWh/10,000 yuan in 2000 to 1630.58 kWh/10,000 yuan in 2018 (see Fig. 2), reaching a peak in 2003. The growth rate of electricity consumption was negative in most years, but positive in 2002, 2003, 2009, 2013, and 2015. The results imply that industrial electricity consumption has decreased overall.

4.2. Spatial distribution of industrial electricity consumption

We used the intensity of electricity consumption in industries to illustrate the spatial distribution of electricity consumption and its change in China between 2003 and 2013 (see Fig. 3). In 2003, cities with a low consumption intensity (<300 kWh/10,000 yuan) are geographically concentrated in the developed coastal regions, such as the Yangtze River Delta area, the Beijing–Tianjin–Hebei region and Guangdong, and scattered about in the central and western regions (e.g., Bayannaoer, Weinan, Ordos, and Haikou), which have fewer industries and smaller populations, while cities with high power consumption are mainly located in the developing inland regions in the center and west. However, in 2008, the number of cities with low electricity consumption in the eastern coastal regions declined, while electricity consumption in some cities in Shanxi, Hebei, Fujian, and Zhejiang increased significantly. In 2013, the concentration of cities with either low or high consumption became more evident. Most cities with low consumption are concentrated in the western provinces (e.g., Gansu and Sichuan) and parts of the eastern coastal areas, whereas cities with high consumption are mainly the western cities and

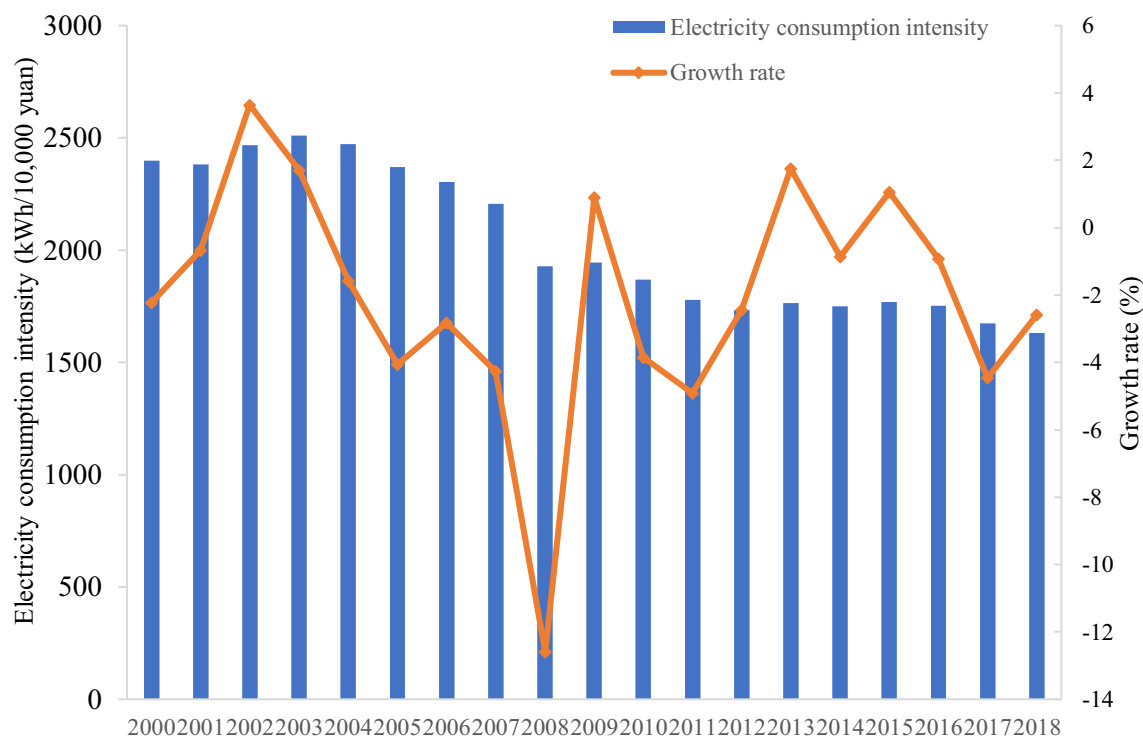
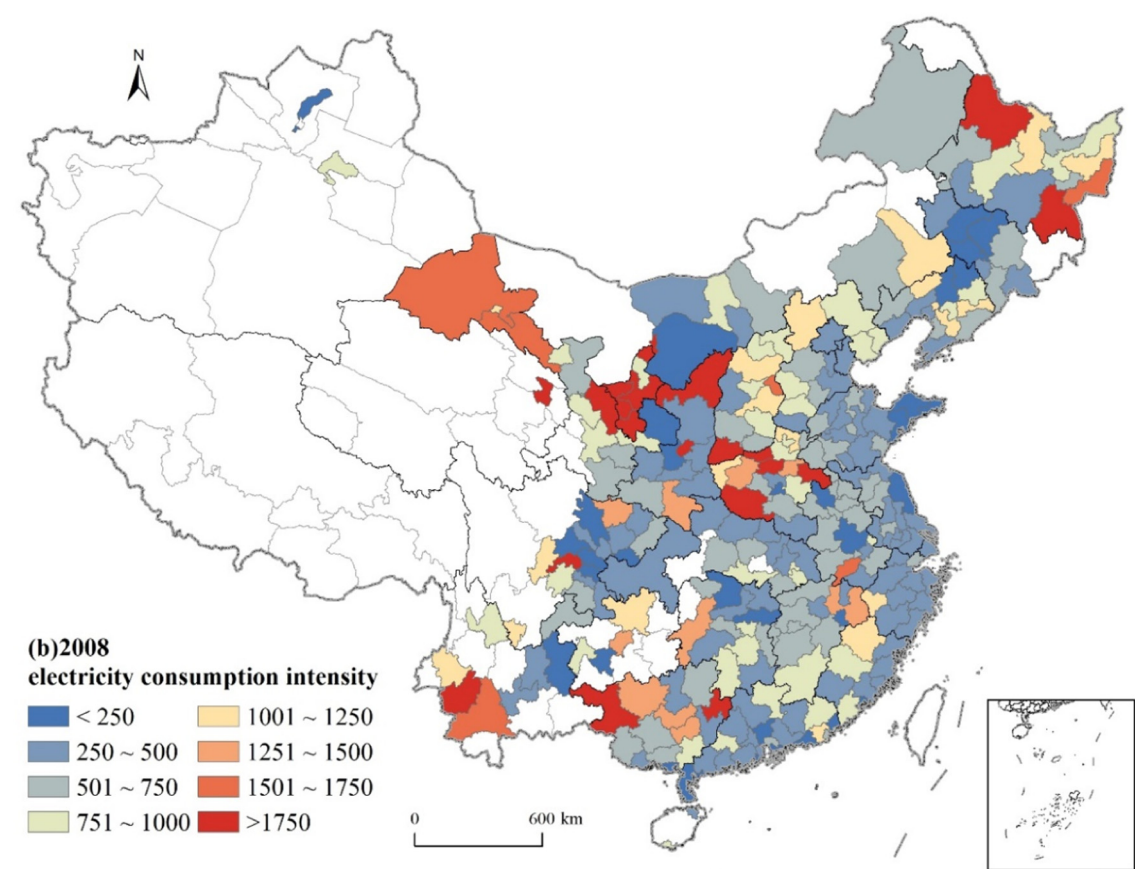
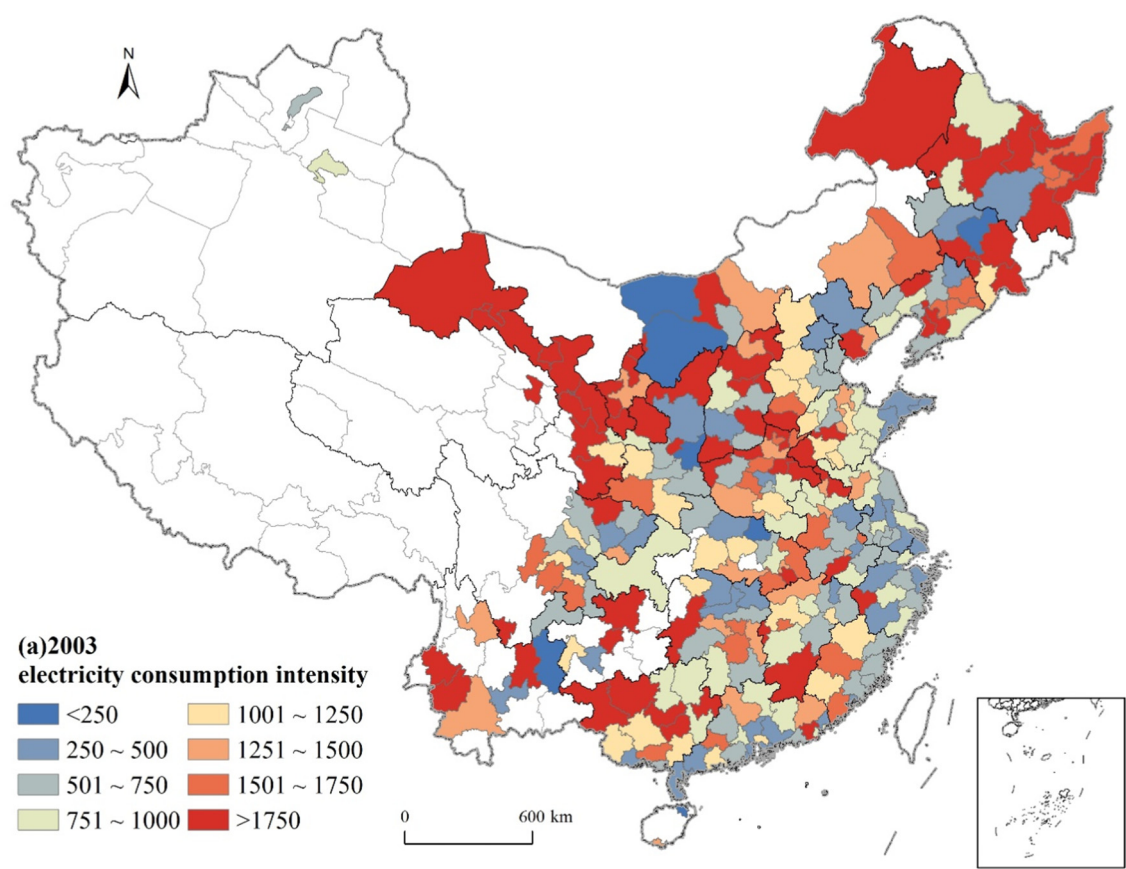


Fig. 2. Change in industrial electricity consumption in China.
Source: China Statistical Yearbook.



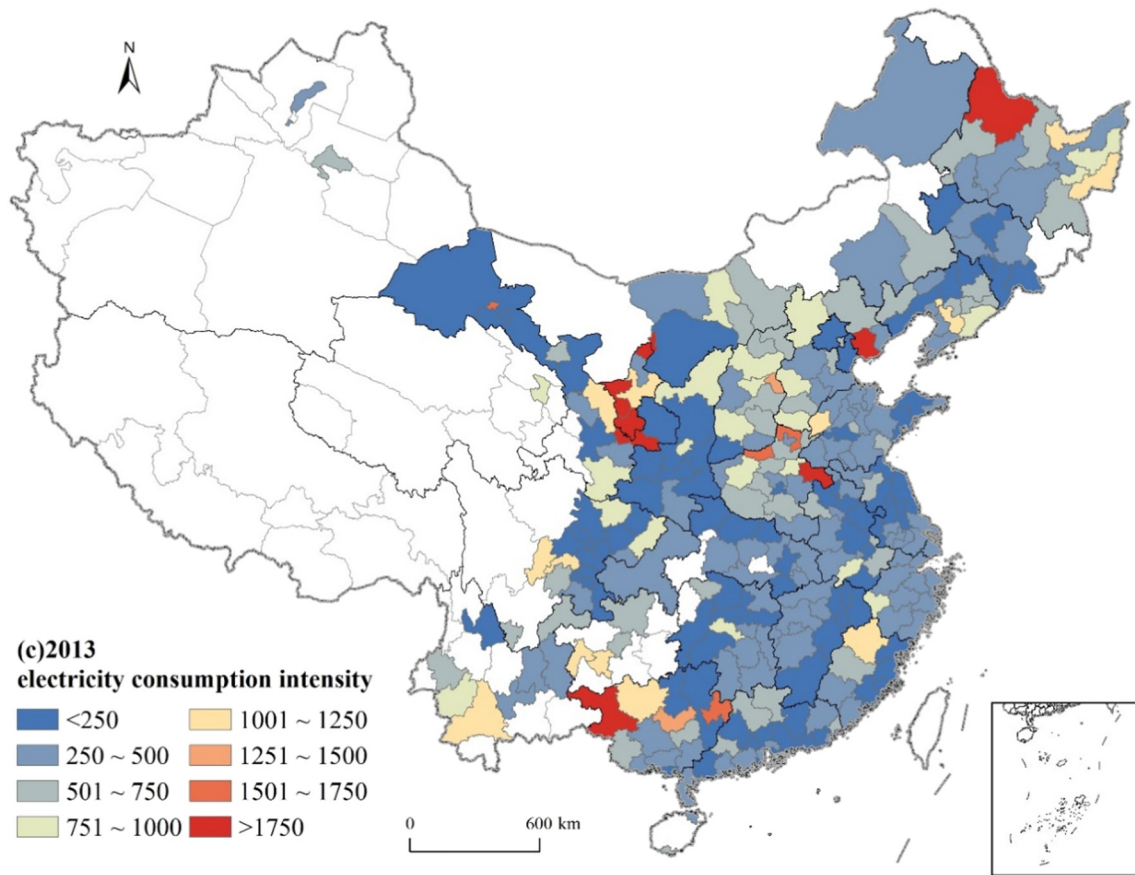


Fig. 3. Spatial pattern of industrial electricity consumption intensity, 2003, 2008, and 2013 (Unit: kWh/10,000 yuan).

parts of the cities of Shanxi in the central region. The change in the distribution of electricity consumption may be related to regional development and the internal structure of industrial agglomeration.

5. Empirical results

With panel data of China's 285 cities during 2003–2013, we adopted the SDM to investigate the spatial impacts of industrial agglomeration on energy consumption by highlighting multiple agglomeration types, and we further explored the spatial heterogeneity effects across regions. Based on the correlation analysis presented in Appendix Table A.1, the strong correlation between different types of agglomeration made it necessary to examine their effects on energy consumption separately. The variance inflation factors in all models are <4 , signifying that there are no serious collinear problems. Furthermore, the significant F -statistic and R^2 values demonstrate that all models are significant and have strong explanatory power.

To determine whether to choose the fixed effect or random effect of SDM, the estimated values of the Hausman test for all the models disprove the null hypothesis that fixed effects are independent of regression variables and favor the fixed effect is better than the random effect. In addition, R^2 and LogL of the time-fixed effect model exceed those of other models, indicating that the time-fixed effect is more in line with objective reality. Therefore, this paper uses the time-fixed effect of the SDM model for regression analysis.

Compared with the estimated coefficients of the non-spatial model (FE) and SDM, it can be seen from Table 2 that the signs of estimates of the variables from FE are mostly consistent with those of SDM but the magnitude of which is larger, due to the influence of explanatory variables

is overestimated when the spatial effect of variable is neglected. In this case, we mainly discuss the estimations of SDM below.

5.1. Effects of industrial agglomeration on energy consumption

The results of the non-spatial mode (FE) and SDM with time-fixed effect that multiple types of industrial agglomeration affect energy consumption are reported in Table 2. Several initial pieces of evidence are found. First, the spatial dependence parameter ρ is positive significantly, indicating that the more (less) the consumption of energy in proximal regions, the more (less) the energy consumption of a particular region. In other words, energy consumption in the local area has a positive spillover effect on that of neighboring areas. Second, several types of industrial agglomeration exhibit different roles in energy consumption, similar to their effects on environmental pollution (Cai and Hu, 2022). Third, it is also possible to note that the spatial lag coefficients of industrial agglomeration indicators are statistically significant or present unexpected values, which implies that the neighbor's industrial agglomeration evidently acts on spatial interactions and spillovers.

Considering the spatial dependence effect is incorporated in the model. That is, a change in an explanatory variable for a single spatial unit has a direct impact on the dependent variable at the same location and could indirectly affect the dependent variable at different locations. As proposed by LeSage and Pace (2009), the direct, indirect, and total effects were computed to correct the interpretation of the SDM coefficients in Table 3. In this case, the marginal direct effects of the dependent variables capture the spatial feedback effects caused by variation in the determinants of energy consumption, slightly unlike the estimated coefficients. In addition, the indirect effect expresses the spatial spillover effect.

Table 2
Influences of industrial agglomeration on energy consumption.

	M1		M2		M3	
	FE	SDM	FE	SDM	FE	SDM
<i>den</i>	−0.547*** (0.0118)	−0.185*** (0.0151)				
<i>pro</i>	0.00385 (0.00702)	0.0181 (0.0123)				
<i>rzi</i>			−0.0000116 (0.000347)	0.000741* (0.000408)	0.0000497 (0.000347)	0.000997** (0.000401)
<i>rdi</i>			−0.276*** (0.0951)	−0.230*** (0.0727)		
<i>rv</i>					−0.206*** (0.0642)	−0.142*** (0.0395)
<i>uv</i>					0.322*** (0.0865)	0.366*** (0.0601)
<i>pop</i>	0.638*** (0.0426)	0.155*** (0.0262)	0.0265 (0.0543)	−0.0921*** (0.0170)	0.0232 (0.0542)	−0.0813*** (0.0169)
<i>open</i>	−0.0250 (0.0438)	−0.244*** (0.0549)	−0.00191 (0.0589)	−0.301*** (0.0564)	−0.0185 (0.0587)	−0.309*** (0.0553)
<i>tec</i>	0.00188 (0.0126)	−0.0223 (0.0238)	−0.309*** (0.0145)	−0.104*** (0.0233)	−0.301*** (0.0145)	−0.0942*** (0.0229)
<i>er</i>	0.0203 (0.0147)	0.0605** (0.0267)	−0.0114 (0.0197)	0.0499* (0.0272)	−0.0118 (0.0198)	0.0476* (0.0268)
<i>str</i>	0.00380 (0.00323)	−0.00523** (0.00254)	0.0383*** (0.00421)	0.00716*** (0.00256)	0.0360*** (0.00423)	0.00290 (0.00250)
Cons	9.160*** (0.403)		8.244*** (0.543)		7.912*** (0.550)	
<i>Wden</i>		0.713*** (0.151)				
<i>Wpro</i>		0.642*** (0.147)				
<i>Wrzi</i>				0.00832 (0.00792)		0.0204*** (0.00790)
<i>Wrdi</i>				−3.345*** (0.974)		
<i>Wrv</i>						−2.886*** (0.450)
<i>Wuv</i>						−2.774** (1.121)
<i>Wpop</i>		−1.244*** (0.282)		0.0589 (0.166)		0.482*** (0.174)
<i>Wopen</i>		−1.087** (0.459)		−0.0418 (0.447)		0.869* (0.445)
<i>Wtec</i>		−0.0805 (0.165)		0.265 (0.165)		0.653*** (0.169)
<i>Wer</i>		0.0141 (0.687)		0.409 (0.693)		0.356 (0.679)
<i>Wstr</i>		0.00644 (0.0337)		−0.0732** (0.0330)		−0.0249 (0.0335)
Time-fixed effect		✓		✓		✓
<i>N</i>	3135	3135	3135	3135	3135	3135
<i>R</i> ²	0.532	0.010	0.158	0.002	0.161	0.003
ρ		0.701*** (0.0789)		0.686*** (0.0826)		0.455*** (0.125)
λ		1.015*** (0.0257)		1.063*** (0.0269)		1.026*** (0.0259)
Log-likelihood		−4480.16		−4551.88		−4490.98
<i>AIC</i>		9035.3		9163.2		9082.0
<i>BIC</i>		9186.6		9314.4		9257.4

Standard errors in parentheses.

* $p < 0.1$.

** $p < 0.05$.

*** $p < 0.01$.

Regarding spatial agglomeration types, the negative and significant coefficient of the direct effect of *den* in M1 is significantly negative, indicating that the industrial agglomeration density has a negative association with local energy consumption. That is, higher density clustering across industries promotes the reduction of energy consumption, which is consistent with the opinion of [Ciccone and Hall \(1996\)](#) that the density of economic activities facilitates increasing returns and enhanced productivity by scale effects. The geographical clustering of industries has a positive scale effect by reducing transportation and resource costs and boosting productivity,

further increasing energy utilization efficiency and reducing energy consumption. But the insignificant coefficient of its indirect effect shows no spillover effects of agglomeration density on the surrounding area. Moreover, the direct and indirect impact estimates of *por* are both positive and significant, meaning that the geographical proximity of industries is more likely related to industrial energy consumption, regardless of local or neighboring areas. This result probably provides empirical support for the opinion that geographical proximity matters for knowledge spillover and technology innovation ([Gallié, 2009](#); [Peng et al., 2021](#)).

Table 3
Direct and indirect impacts of multiple types of industrial agglomeration.

	M1_SDM			M2_SDM			M3_SDM		
	Direct	Indirect	Total	Direct	Indirect	Total	Direct	Indirect	Total
<i>den</i>	−0.166*** (0.0149)	−0.313 (0.293)	−0.478 (0.294)						
<i>pro</i>	0.0240** (0.0122)	1.804** (0.881)	1.828** (0.883)						
<i>rzi</i>				0.000750* (0.000437)	0.00849 (0.0294)	0.00924 (0.0295)	0.000887** (0.000419)	0.00265 (0.0155)	0.00354 (0.0156)
<i>rdi</i>				−0.248*** (0.0710)	−12.03** (5.106)	−12.28** (5.121)			
<i>rv</i>							−0.170*** (0.0383)	−3.611*** (1.091)	−3.780*** (1.094)
<i>uv</i>							0.408*** (0.0583)	−2.285 (2.380)	−1.876 (2.392)

Regarding the effects of localization and diversity on energy consumption in M2, the estimate of direct impact for *rzi* and energy consumption is significantly negative, while the indirect effect is positive but not significant. That is to say, in line with previous studies (Chen et al., 2018; Yang et al., 2020), the externality of localization agglomeration contributes to reducing local energy consumption, but not to surrounding regions. By contrast, in line with the results, the negative and significant estimated coefficient of *rdi* implies that diversity agglomeration helps lower energy consumption. Energy-saving measures in China's industrial sector may benefit from knowledge spillovers and technological innovation through the interaction between different industries.

Finally, we broke down industrial diversity into related variety and unrelated variety based on documents in Section 2. In M3, the coefficients of the direct and indirect impacts of *rzi* are both positive but the latter is insignificant, in contrast to the corresponding result of M2. Direct and indirect estimates of *rv* are significant and negative at the 1 % level. Related variety has a significant negative influence on local energy consumption and a positive spillover effect on reducing energy consumption in neighboring areas as well. By contrast, the positive significantly estimates of direct effect of *uv* show a positive impact, the magnitude of which is larger than that of related variety. The statistical results imply that energy consumption benefits from knowledge spillover and technological innovation between technologically related industries. However, the fierce competition for input products, including fossil fuels, may increase energy utilization for unrelated variety. Furthermore, the negative role of the unrelated variety is greater than the positive role of the related variety in reducing energy consumption. The similar effects of related and unrelated variety on other aspects, including entrepreneurship and the manufacturing sector's survival, are presented by Guo et al. (2016) and Basile et al. (2017). Our results provide additional empirical evidence from China to capture the effectiveness of agglomeration types-related variety and unrelated variety on energy consumption.

5.2. Heterogeneity test

The different levels of economic development and population sizes across China's 285 cities may induce heterogeneity effects in geography. Therefore, considering the heterogeneities of industrial agglomeration degree and energy consumption in China's sub-regional areas, we further examined the heterogeneous spatial effects of industrial agglomeration on energy consumption across regions. Two kinds of sub-regions are classified in our paper: One is the coastal region and inland region according to development level (region scale),¹ and the other classification is major city and small and medium-sized cities according to whether the population of urban residents is >100 million (city size). In this context, we further tested

the relationship between industrial agglomeration and energy consumption in these sub-regional areas.

5.2.1. Region scale test

According to the estimated results presented in Table 4, there are significant differences in the direct and indirect effects of industrial agglomeration on energy consumption between coastal and inland regions according to the types of agglomeration. The results imply that the increase in agglomeration density is conducive to declining local energy consumption in both coastal and inland cities and that its contribution is larger in coastal regions than in inland. Meanwhile, the negatively spatial spillover effect of density is larger in coastal regions than inland. Nevertheless, the proximity of industries impairs the reduction of energy utilization in the coastal region while having an evident spatial spillover effect for inland region, based on the significant positive coefficient of the direct effect of *pro* for coastal regions and that of its indirect effect inland. Localized agglomeration presents similar effects in the two regions. Diversified agglomeration can effectively reduce local energy consumption in coastal regions but for neighboring regions of inland through spatial spillover effect. The related variety has energy-saving effects for locals and neighbors in inland regions, while it just has the negative spillover effect for coastal regions. However, the clustering of unrelated industries has an improvement effect on local energy consumption for coastal regions and a negative spillover effect, while there is an exaggerated effect for inland regions.

In summary, agglomeration types, such as spatial density, diversity, and unrelated variety play a supporting role in reducing energy consumption in coastal regions, while density and related variety have similar effects in inland regions. Moreover, proximity and localized agglomeration have exaggerated effects on energy consumption in coastal regions and the same goes for the role of unrelated variety inland. In coastal regions, industrial agglomeration has occurred on a large scale and is in an advantaged stage of the industrial life cycle (Neffke et al., 2011). The positive externalities of diversification agglomeration in saving energy consumption are dominant in coastal regions, with knowledge and technological spillover between diversified industries. For inland regions, agglomeration appeared recently and is in an initial phase for agglomeration of specialized industries. Therefore, geographical proximity and local specialization in their own industries can generate more benefits to reduce energy consumption.

Furthermore, the significant spatial spillover effects for coastal regions are associated with density, related variety, and unrelated variety. Comparatively, spatial spillover effects in inland regions are explained by other types of agglomeration excluding the unrelated variety, the whole of which is more evident than that of coastal areas. The evident spatial spillover effect indicates that the flow of elements is active between regions in inland areas (Han et al., 2018a), but the overestimated values may be related to the overly different size and number between coastal and inland areas.

5.2.2. City size test

Table 5 shows the direct and indirect effects of industrial agglomeration on energy consumption across sub-regions based on city size.

¹ The coastal regions are Beijing, Tianjin, Shanghai, and the provinces of Liaoning, Hebei, Shandong, Jiangsu, Zhejiang, Fujian, Guangdong, and Haikou; the other regions are in the inland area.

Table 4

Direct and indirect effects of industrial agglomeration across regions.

		Coastal area			Inland area		
		Direct	Indirect	Total	Direct	Indirect	Total
M1	<i>den</i>	−0.225*** (0.0227)	0.572*** (0.193)	0.347* (0.186)	−0.157*** (0.0205)	1.119* (0.576)	0.963* (0.576)
	<i>pro</i>	0.0497*** (0.0166)	−0.0428 (0.0894)	0.00684 (0.0880)	0.0221 (0.0156)	2.154*** (0.632)	2.176*** (0.634)
M2	<i>rzi</i>	0.00546*** (0.00135)	−0.0120 (0.00981)	−0.00654 (0.00999)	0.000711 (0.000509)	0.0389* (0.0231)	0.0396* (0.0233)
	<i>rdi</i>	−0.439*** (0.0713)	−0.422 (0.450)	−0.861* (0.447)	0.169 (0.126)	−7.805* (4.528)	−7.636* (4.560)
M3	<i>rzi</i>	0.00638*** (0.00135)	0.00380 (0.00917)	0.0102 (0.00939)	0.000717 (0.000488)	0.0292* (0.0162)	0.0299* (0.0163)
	<i>rv</i>	−0.0599 (0.0447)	−1.368*** (0.293)	−1.428*** (0.292)	−0.223*** (0.0534)	−5.821*** (1.885)	−6.044*** (1.894)
	<i>uv</i>	−0.181** (0.0816)	1.866*** (0.590)	1.685*** (0.607)	0.595*** (0.0778)	−2.255 (2.168)	−1.660 (2.195)

Table 5

Direct and indirect effects based on city-size.

		Major cities			Small-medium cities		
		Direct	Indirect	Total	Direct	Indirect	Total
M1	<i>den</i>	−0.897*** (0.164)	−0.897*** (0.164)	−2.081*** (0.284)	−0.146*** (0.0187)	0.954** (0.372)	0.808** (0.369)
	<i>pro</i>	0.0965 (0.0647)	0.0965 (0.0647)	−0.104 (0.132)	0.00831 (0.0143)	0.401 (0.330)	0.409 (0.330)
M2	<i>rzi</i>	0.00370** (0.00146)	−0.0207*** (0.00688)	−0.0170** (0.00731)	0.000188 (0.000474)	0.00649 (0.0135)	0.00668 (0.0136)
	<i>rdi</i>	−2.118*** (0.483)	−1.065 (1.434)	−3.183* (1.736)	0.165 (0.115)	−2.503 (3.473)	−2.337 (3.497)
M3	<i>rzi</i>	0.00319*** (0.00119)	−0.00776 (0.00547)	−0.00456 (0.00553)	0.000337 (0.000467)	0.0109 (0.0116)	0.0113 (0.0117)
	<i>rv</i>	−1.677*** (0.186)	0.210 (0.568)	−1.467** (0.583)	−0.151*** (0.0455)	−3.885*** (1.219)	−4.036*** (1.222)
	<i>uv</i>	0.137 (0.439)	1.010 (0.937)	1.147 (1.190)	0.421*** (0.0709)	−0.991 (1.795)	−0.570 (1.817)

Spatial density has a significant positive impact on reducing energy consumption in both major and small and medium-sized cities. The improvement effect of the agglomeration density is greater in major cities than in small and medium-sized cities. Localized agglomeration in major cities can increase energy consumption, but diversity and related variety have an improvement effect. Localization and diversity do not have a significant effect in major cities, while related variety has a reducing effect, which is greater than it is in small and medium-sized cities. The unrelated variety has a significantly aggravating effect on small and medium-sized cities. In addition, for major cities, indirect effects reveal the same spatial spillover effect for density and localized agglomeration. The density (positive) and related variety (negative) generate the inverse spatial spillover effect in small and medium-sized cities.

As shown, the energy-saving effects of agglomeration (e.g., density and related variety) mainly in both types of cities, and diversity only occurs in major cities. While the aggravating effects of localization and unrelated variety are found in major cities and small and medium-sized cities, separately. The higher level of urbanization in major cities causes more positive externality from diversified agglomeration through the increasing economies scale effect and knowledge spillover effect across various industries, even the spatial spillover effects. In terms of small and medium-sized cities, industrial agglomeration of industries exerts more positive externalities and spatial spillover effects based on clustering of localized or related industries, due to the young stage of industrial agglomeration. The direct effects of industrial agglomeration are basically consistent with that of the region scale test and their roles in environmental pollution (Shen and Peng, 2020), while the spatial spillover effects conform to reality.

5.3. Robustness check

To check the robustness of the above results, we replaced the electrical energy consumption intensity of all the industries in each city with the indicator of the top seventeen industries² with high energy consumption of each city as dependent variables. In this regard, we conducted a similar procedure as mentioned above. As expected, the results hold for all models, and even the estimated results are more significant. All results are reported in Appendix Tables A.2–A.5.

6. Conclusions

The externalities of agglomeration on energy consumption are not as simple as imagined, and they simply concern the effects of localization and diversity. It is necessary to take other types of agglomeration in space and organization into account and consider their potential spatial effects as well (Beaudry and Schiffauerova, 2009; Caragliu et al., 2016). Furthermore, with the development of transportation and communication, elements enable flow across larger scopes. The interaction between industrial agglomeration and energy consumption may be more complicated in the space-temporal dimension. The spatial interaction between industrial agglomeration and energy consumption should also be explored.

Hence, the present research attempted to cover all agglomeration types by involving the initial spatial concentration and refining diversity into related variety and unrelated variety derived from Evolutionary Economy Geography. Next, with a SDM approach, we discussed the spatial interaction

² The top seventeen industries with high electricity consumption are defined based on industrial consumption intensity in 2016.

between industrial agglomeration and energy consumption by China's industries based on the agglomeration types and the heterogeneity effects across regions during 2003–2013, using a spatial econometric approach. Specifically, this empirical approach allows one to estimate the impact of variables associated with neighboring regions on the energy consumption of a specific region, capturing spatial interdependence among regions. Beyond that, the additional test for different regions accounts for the spatial heterogeneity effects.

Some findings are shown in our empirical analysis below. First, consistent with **Hypothesis 1**, all types of industrial agglomeration, as a whole, are important in interpreting energy consumption. Specifically, spatial density has significant supportive effects on reducing energy consumption, while geographical proximity shows the inverse effects. Unlike the significantly aggravated effect of localization, diversity is conducive to energy conservation. Meanwhile, related variety plays the same energy-saving role as diversity, while unrelated variety increases consumption. The positive and negative effects of the two types of diversity on energy consumption are in line with their roles in other economic activities, including the survival and entrepreneurship of manufacturing sectors (Basile et al., 2017; Guo et al., 2016).

In addition, as expected in our **Hypothesis 2**, energy consumption exerts spatial dependence directly, and geographical proximity, diversity, and related variety evidently show spatial spillover effects, almost all signs of which are consistent with their direct effect. Among them, geographical proximity harms energy consumption in the neighboring regions. Unlike the positive but insignificant spatial spillover effect of unrelated variety, diversity and related variety presents the promoted effect on energy conservation for neighboring areas. It can be seen that there is a spatial dependence between industrial agglomeration and energy consumption across regions, consistent with the empirical evidence of Yang et al. (2020).

Furthermore, the heterogeneity effects of industrial agglomeration are evident across regions, regardless of whether it is based on regional development (region scale) or urbanization level (city size). Except for the stability-saving effect of spatial density for the four regions, diversity has a significantly reduced effect on energy consumption in coastal areas and major regions, and related variety and unrelated variety have a similar effect for coastal areas and the latter, separately. By contrast, related variety has an improving effect, while unrelated variety presents an aggravating effect in inland and small and medium-sized cities. This means that the discrepant externalities of agglomeration accompany the different stages of their life cycles, confirming the opinion of Neffke et al. (2011). Therefore, diversity and one of its decomposition-related variety have a consumption-saving effect during the initial and advanced stages of agglomeration, whereas the effect of unrelated varieties changes obviously over the life cycle.

The following suggestions are offered according to our findings. On the one hand, planning industrial parks and development zones to drive industrial agglomeration has become a way for local governments to promote local economic growth in Chinese cities. Therefore, in addition to improving the density of agglomeration and clustering different industries, this study suggests that paying more attention to the link between industries introduced and avoiding the concentration of single or unrelated industries will likely be more effective for growth and energy conservation, no matter for local areas

or neighbors. In addition, the spillover effects between regions recommend that deepening interregional cooperation in industrial development and energy conservation and emission reduction is beneficial for promoting the integrated development of interregional planning and supervision.

On the other hand, heterogeneity strategies should be formulated according to the stages and structure of industry development and the differentiated effects of industrial agglomeration as well at the regional and city scale. Inland and medium-sized cities in central and western regions should increase the scale of industrial agglomeration and strengthen industrial relatedness, considering that industrial development is in the initial stage. As regards developed areas in eastern cities or coastal areas, where industrial agglomeration is in the advanced stage of the industrial life cycle, the positive externality of diversity and unrelated variety are dominant by the spillover effect of knowledge and technology. Hence, policymakers can promote industrial transformation and upgrade industrial agglomeration structures by investing heavily in scientific and technological research and development and encouraging companies to adopt the latest production technology, thus supporting the green development of industries.

Some limitations of this research remain that merit future analysis. First, due to data accessibility, our sample is limited from 2003 to 2013. Although the validity of our conclusions is not time sensitive, it is noteworthy that the main aim was to uncover the heterogeneity effects of the agglomeration types. However, the updated data should be used to test the reliability of our conclusions. Second, our paper primarily examines the spatial effects of multiple types of industrial agglomeration on energy consumption and their heterogeneity effects across regions. The potential mechanism would be undertaken in order to facilitate a deeper understanding of their relationship.

CRediT authorship contribution statement

Yuanyuan Cai: Conceptualization, Methodology, Data curation, Software, Visualization, Validation, Writing – Original draft preparation, Review, Rewriting & Editing.

Zhiqiang Hu: Conceptualization, Data curation, Visualization, Writing - Original draft preparation, Review.

Data availability

Data will be made available on request.

Declaration of competing interest

The authors declare no conflict of interest.

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Appendix A

Table A.1

Correlation coefficients of independent variables.

	<i>den</i>	<i>pro</i>	<i>rzi</i>	<i>rdi</i>	<i>rv</i>	<i>uv</i>
<i>den</i>	1					
<i>pro</i>	0.0008	1				
<i>rzi</i>	−0.120	−0.0189	1			
<i>rdi</i>	0.110	−0.108	−0.0848	1		
<i>rv</i>	0.292	−0.0786	−0.0849	0.555	1	
<i>uv</i>	0.121	−0.0405	−0.0661	0.359	0.468	1

Table A.2
Robustness for the effects of industrial agglomeration.

	M1r		M2r		M3r	
	FE	SDM	FE	SDM	FE	SDM
<i>den</i>	−0.0132*** (0.00186)	0.00907*** (0.00333)				
<i>pro</i>	−0.00222** (0.00112)	0.0104*** (0.00272)				
<i>rzy</i>			0.0000653 (0.0000414)	0.000124 (0.0000872)	0.0000974** (0.0000401)	0.000150* (0.0000838)
<i>rdi</i>			−0.0697*** (0.0112)	−0.136*** (0.0155)		
<i>rv</i>					−0.114*** (0.00743)	−0.140*** (0.00824)
<i>uv</i>					0.0473*** (0.00993)	0.0544*** (0.0125)
<i>pop</i>	0.0158** (0.00682)	−0.0392*** (0.00577)	−0.000905 (0.00649)	−0.0269*** (0.00364)	−0.00501 (0.00629)	−0.0163*** (0.00353)
<i>open</i>	−0.0125* (0.00658)	−0.0533*** (0.0121)	−0.00823 (0.00660)	−0.0352*** (0.0120)	−0.00859 (0.00638)	−0.0236** (0.0115)
<i>tec</i>	0.000779 (0.00203)	−0.0138*** (0.00523)	−0.00691*** (0.00175)	−0.00825* (0.00496)	−0.00501*** (0.00170)	−0.00333 (0.00479)
<i>er</i>	0.00710*** (0.00239)	0.0174*** (0.00586)	0.00695*** (0.00239)	0.0169*** (0.00581)	0.00905*** (0.00232)	0.0167*** (0.00560)
<i>str</i>	−0.00131*** (0.000502)	−0.00464*** (0.000558)	−0.000397 (0.000490)	−0.00361*** (0.000547)	−0.00128*** (0.000477)	−0.00309*** (0.000522)
<i>Cons</i>	(0.0683)		(0.0644)		(0.0635)	
<i>Wden</i>		0.0620* (0.0341)				
<i>Wpro</i>		0.120*** (0.0327)				
<i>Wpop</i>		0.0114 (0.0628)		0.119*** (0.0355)		0.170*** (0.0368)
<i>Wopen</i>		−0.389*** (0.103)		−0.238** (0.0955)		−0.00695 (0.0929)
<i>Wtec</i>		−0.0109 (0.0362)		−0.00481 (0.0353)		0.0772* (0.0357)
<i>Wer</i>		−0.0881 (0.151)		−0.132 (0.148)		−0.154 (0.142)
<i>Wstr</i>		0.0137* (0.00751)		0.00246 (0.00714)		0.00391 (0.00712)
<i>Wrzy</i>				−0.00316* (0.00170)		−0.00259 (0.00166)
<i>Wrdi</i>				0.293 (0.207)		
<i>Wrv</i>						−0.263*** (0.0964)
<i>Wuv</i>						−0.125 (0.234)
Time-fixed effect		✓		✓		✓
<i>N</i>	3135	3135	3135	3135	3135	3135
<i>R</i> ²	0.025	0.011	0.022	0.102	0.084	0.169
<i>ρ</i>		0.538*** (0.107)		0.626*** (0.0915)		0.295** (0.139)
<i>λ</i>		0.0491*** (0.00124)		0.0484*** (0.00123)		0.0448*** (0.00113)
Log-likelihood		271.178		292.211		420.1542
<i>AIC</i>		−510.356		−552.421		−804.308
<i>BIC</i>		−413.549		−455.615		−695.4014

Standard errors in parentheses.

* $p < 0.1$.

** $p < 0.05$.

*** $p < 0.01$.

Table A.3
Robustness for direct and indirect impacts of multiple types of industrial agglomeration.

	M1r_SDM			M2r_SDM			M3r_SDM		
	Direct	Indirect	Total	Direct	Indirect	Total	Direct	Indirect	Total
<i>den</i>	0.00962*** (0.00336)	0.146* (0.0771)	0.155** (0.0764)						
<i>pro</i>	0.0112*** (0.00261)	0.288*** (0.0956)	0.299*** (0.0958)						
<i>rzy</i>				0.0000987 (0.0000919)	−0.00871* (0.00494)	−0.00861* (0.00497)	0.000146* (0.0000868)	−0.00357 (0.00263)	−0.00342 (0.00265)

Table A.3 (continued)

	M1r_SDM			M2r_SDM			M3r_SDM		
	Direct	Indirect	Total	Direct	Indirect	Total	Direct	Indirect	Total
<i>rdi</i>				−0.134*** (0.0150)	0.628 (0.604)	0.494 (0.605)			
<i>rv</i>							−0.141*** (0.00794)	−0.457*** (0.170)	−0.598*** (0.170)
<i>uv</i>							0.0554*** (0.0122)	−0.181 (0.369)	−0.125 (0.372)

Table A.4

Robustness for direct and indirect effects of industrial agglomeration across region-scale.

		Coastal area			Inland area		
		Direct	Indirect	Total	Direct	Indirect	Total
M1	<i>den</i>	−0.0142** (0.00585)	−0.00313 (0.0425)	−0.0173 (0.0403)	0.0162*** (0.00433)	0.207*** (0.0610)	0.224*** (0.0605)
	<i>pro</i>	0.00735* (0.00427)	−0.00238 (0.0213)	0.00496 (0.0208)	0.0112*** (0.00323)	0.203*** (0.0490)	0.214*** (0.0490)
M2	<i>rzi</i>	0.00190*** (0.000328)	−0.00215 (0.00251)	−0.000246 (0.00256)	0.0000870 (0.000101)	0.00173 (0.00255)	0.00182 (0.00257)
	<i>rdi</i>	−0.0966*** (0.0175)	0.335*** (0.112)	0.00344 (0.00234)	−0.170*** (0.0255)	−1.355** (0.539)	0.00114 (0.00146)
M3	<i>rzi</i>	0.00217*** (0.000315)	0.00128 (0.00229)	0.239** (0.112)	0.000115 (0.0000951)	0.00103 (0.00144)	−1.525*** (0.543)
	<i>rv</i>	−0.122*** (0.0105)	−0.0992 (0.0620)	−0.221*** (0.0618)	−0.147*** (0.0107)	−0.254** (0.122)	−0.401*** (0.122)
	<i>uv</i>	0.0679*** (0.0189)	0.606*** (0.146)	0.674*** (0.150)	0.0621*** (0.0152)	−0.855*** (0.230)	−0.793*** (0.233)

Table A.5

Robustness for direct and indirect effects of industrial agglomeration across city-size.

		Major cities			Small and medium-size cities		
		Direct	Indirect	Total	Direct	Indirect	Total
M1	<i>den</i>	−0.897*** (0.164)	−1.184*** (0.322)	−2.081*** (0.284)	−0.146*** (0.0187)	0.954** (0.372)	0.808** (0.369)
	<i>pro</i>	0.0965 (0.0647)	−0.201 (0.141)	−0.104 (0.132)	0.00831 (0.0143)	0.401 (0.330)	0.409 (0.330)
M2	<i>rzi</i>	0.00370** (0.00146)	−0.0207*** (0.00688)	−0.0170** (0.00731)	0.000188 (0.000474)	0.00649 (0.0135)	0.00668 (0.0136)
	<i>rdi</i>	−2.118*** (0.483)	−1.065 (1.434)	−3.183* (1.736)	0.165 (0.115)	−2.503 (3.473)	−2.337 (3.497)
M3	<i>rzi</i>	0.00319*** (0.00119)	−0.00776 (0.00547)	−0.00456 (0.00553)	0.000337 (0.000467)	0.0109 (0.0116)	0.0113 (0.0117)
	<i>rv</i>	−1.677*** (0.186)	0.210 (0.568)	−1.467** (0.583)	−0.151*** (0.0455)	−3.885*** (1.219)	−4.036*** (1.222)
	<i>uv</i>	0.137 (0.439)	1.010 (0.937)	1.147 (1.190)	0.421*** (0.0709)	−0.991 (1.795)	−0.570 (1.817)

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