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# Industrial Spatial Agglomeration Using Distance-based Approach in Beijing, China

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**Abstract:** To study the difference of industrial location among different industries, this article is to test the spatial agglomeration across industries and firm sizes at the city level. Our research bases on a unique plant-level data set of Beijing and employs a distance-based approach, which considers space as continuous. Unlike previous studies, we set two sets of references for service and manufacturing industries respectively to adapt to the investigation in the intra-urban area. Comparing among eight types of industries and different firm sizes, we find that: 1) producer service, high-tech industries and labor-intensive manufacturing industries are more likely to cluster, whereas personal service and capital-intensive industries tend to be randomly dispersed in Beijing; 2) the spillover of the co-location of firms is more important to knowledge-intensive industries and has more significant impact on their allocation than business-oriented services in the intra-urban area; 3) the spatial agglomeration of service industries are driven by larger establishments, whereas manufacturing industries are mixed.

**Keywords:** distance-based approach; spatial agglomeration; intra-urban area; Beijing

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## 1 Introduction

As early as 1890, industrial cluster has drawn attentions from economists and geographers. Marshall (1890) used the concept of externalities to shed light on the advantages of proximity for production. Since then, such external effects have gradually been recognized in the explanations of industrial location. New economic geography is exactly based on Marshallian externalities to predict how firm agglomeration creates increasing return (Fujita, 1988; Krugman, 1991a; 1991b; Venables, 1996). In addition, the success of some clusters, such as 'Third Italy' and Silicon Valley, has confirmed the theoretical link between economic agglomeration and regional growth in practice. Therefore, there has been a renewed interest in industrial agglomeration since the 1990s.

There is no doubt that the most striking feature of economic activities is concentration, as Krugman mentioned (1991a). However, there are different focuses on this issue across various disciplines. Most of economists concern the correlation between growth and industrial agglomeration, and a positive correlation was observed by plenty of researches in different countries (Ciccone, 2002; Bertinelli and Decrop, 2005; Brülhart and Sbergami, 2009; Lin *et al*., 2011). However, these studies only calculated the extent of spatial agglomeration but

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ignored other characteristics of agglomeration, such as the spatial scale agglomeration and the discrepancy across sectors. On the contrary, space, place and scale are all at the heart of geographic analysis (Coe *et al*., 2007). From the viewpoint of geography, the spatial scale where industrial agglomeration takes place and the sectoral scope are, at least, as significant as its extent. Furthermore, the study from spatial perspective is helpful to reduce the consumption of nature resources in industrialization process. Indeed, this process has consumed too many land resources in developing countries. For example, establishing a large number of development zones has led to a great loss of agricultural lands in China (Yeh and Li, 1999; Yang and Wang, 2008).

As the importance of the spatial agglomeration is clear, the next problem is how to accurately measure the concentration. In recent years, a variety of indicators and methods have been developed to measure the spatial agglomeration of industry (Haining, 2003; Fischer and Getis, 2009). However, in light of differentiated aims and datasets, there is no consensus regarding what approaches are more appropriate (HUallachain and Leslie, 2009). Generally, these approaches can be classified into two groups: the cluster-based methods which rely on a discrete definition of space and the distance-based methods which are developed to analyze the firm agglomeration in continuous space. The former group uses aggregated data which can be easily collected from official statistics. This implies that individual establishments have been aggregated into discrete spatial units, such as cities or regions. For example, Ellison and Glaeser index (EG index) (1997) is one of the most popular methods which consider space in a discrete manner. This index is believed to measure the extent of industrial agglomeration more accurately than Gini index due to the purge of the plant size effect (Briant *et al*., 2010; Lin *et al*., 2011). Many empirical studies have employed EG index to explain the growth (Braunerhjelm and Borgman, 2004) and found out the factors of industrial agglomeration (Henderson, 2003; Ellison *et al*., 2010; Alfaro and Chen, 2014). However, although EG index can achieve a general extent of spatial agglomeration, they fail to find out where industrial concentration takes place in a given place. Local indicators of spatial association (LISA), such as local Moran′s I, allow the decomposition of general indicators into contributors to each individual observation (Anselin, 1995). These indicators are widely applied to explore whether and where there is an industrial agglomeration in geographic space (Goetz and Rupasingha, 2002; Van and Atzem, 2004; Guillain and Le Gallo, 2010). According to LISA cluster map, high-high clusters or low-low clusters indicate spatial agglomeration (Fischer and Getis, 2009). This method needs a large number of regions to measure spatial cluster, and the agglomeration at the intra-region level has to be ignored. Therefore, Duranton and Overman (2005) argued that aggregating data makes computations simple, but meanwhile, it abandons a large amount of useful information.

The reason of widely using aggregated data is not its high applicability for industrial spatial agglomeration studies, but actually its high accessibility (Glaeser *et al*., 1992; Clark *et al*., 2003; Devereuex *et al*., 2004). Aggregated data are usually collected from a certain administrative region, as mentioned above. Basically, the observations on different levels probably lead to various spatial patterns. In other words, the results are quite sensitive to the shape, size, and position of the areal units, namely the Modifiable Areal Unit Problem (MAUP) (Morphet, 1997; Briant *et al*., 2010). Furthermore, those area units, are usually shaped to meet the administrative needs rather than to reflect the economic relations within the units. Therefore, the spatial scale, population and establishments of the units could be different from each other. The analysis based on these mixed areal units would further conclude misleading results.

To overcome the above weaknesses, many studies recommend the application of some methodologies which consider space as continuous (Marcon and Puech, 2003; Duranton and Overman, 2005; Arbia *et al*., 2008; Logan *et al*., 2011). The most significant characteristic of these methods is that they adopt distance-based and firm-level data. In essence, the benefits firms obtain from co-location gives rise to agglomeration economies. However, a small number of firms hiring a large number of employees may also bring the same effect. Therefore, firm is the better index to measure industrial spatial agglomeration than employment. We can figure out the industrial spatial patterns in continuous space through the analysis of the distance between every pair of the establishments. There are some researches investigating industrial agglomeration where the distance-based methods have been applied. Marcon and Puech (2003) initially introduced distance-based methods (L and D function) to analyze the geographic concentration of industries in Paris. Then they developed the M-function, constituting an extension of Ripley′s functions (Marcon and Puech, 2010). These three methods derived from Ripley′s K function (Ripley, 1976; 1977). Carlos *et al.* (2013) also improved K function through replacing Euclidean distance with street network distance to provide more reliable descriptions in the CBD of metropolitan Toluca. However, the result shows that distance has little influence on most of sectors even at the neighborhood scale. Kernel density is an alternative method. Duranton and Overman (2005) applied K-density to investigate the industrial spatial pattern in the UK and further proposed five fundamental criteria, which characteriz a ′good′ measure of geographic concentration. By contrast with absolute measures used by Ripley′s function, Duranton and Overman chose a relative measure. Specifically, whether a sector is concentrated or not is defined by comparing the distribution of that sector to the whole industry. Barlet *et al*. (2013) also employed this approach in an empirical study on France. The study suggests that for an analysis of the location patterns of services, a distance-based approach is better suited than the traditional EG cluster-based index of spatial agglomeration. While most of literature focus on developing and improving methods, empirical researches are still needed, especially the ones at the city level. In this research, we will follow and improve the method developed by Duranton and Overman to test the industrial spatial pattern in a metropolitan area.

Although some scholars have analyzed the spatial distribution of different industries in Beijing, most of these researches focus one type of industry. Zhang and Chen (2011) employ the Ripley′s K-function to detect urban office space in Beijing. The result shows the employment of these sectors concentrate in *Zhongguancun* Science Park, CBD and Finance Street (*Jinrongjie in Chinese*). Furthermore most of establishments from finance industry confine themselves to the inside of a small area. The obvious tendency of suburbanization of manufacturing industry has been detected (Chen and Li, 2011; Zhang and Sun, 2012). Most of manufacturing establishments move away from the inner city. Some shopping malls have been built up next to the city centre (Zhou and Ji, 2009). It means that Retail do not cluster in the old city in Beijing. Few studies reveal the discrepancy among different types of industries, partly because the data are unavailable.

This article bases on firm data to find out the characteristics of spatial distribution and agglomeration across eight industries and highlight the differences among them in Beijing. Then we further explore the discrepancy of industrial agglomeration resulting from establishment size. These researches are helpful to understand the industrial location in the intra-metropolitan area.

## 2 Data and Methodology

### 2.1 Data

One of the obvious operational problems of the distance-based methodologies is the accessibility of data. It is difficult to get the precise geographic coordinates of each firm which are required by the analyses through these methods. In this research, we employ a unique data set: all registered enterprises in 2010 from the Beijing Administration for Industry and Commerce. For the purpose of firm registration and market supervision, the plant-level data set includes some basic information such as address, industry code and firm′s employment size. Firm′s address is able to convert to the geographic coordinate through the Application Programming Interface (API) from Baidu′s map. According to the geographic coordinate of each firm, we can obtain a map including all firms in SHP file format by ArcGIS 9.3 (Fig. 1). The data set refers to 570 738 firms, including 523 498 service and 47 240 manufacturing enterprises. Obviously, service industry dominates industrial development in Beijing (Table 1).

The study emphasizes on the discrepancy of spatial agglomeration among various industries. The comparison of all industries is time-consuming and unnecessary, so we choose 8 types of typical industries, including producer and personal services, high-tech service and manufacturing industries, labor-intensive and capital-intensive manufacturing industries and equipment manufacturing which demand a large number of labor, capital and technology. To get a strong and comparable result, we adjust the official category of the industries as shown in the following table. For example, business service covers not only some advance service, such as law and consulting, but also some traditional sectors, such as tourism. Thus we remove those sectors to the comparability of researches between in China and in

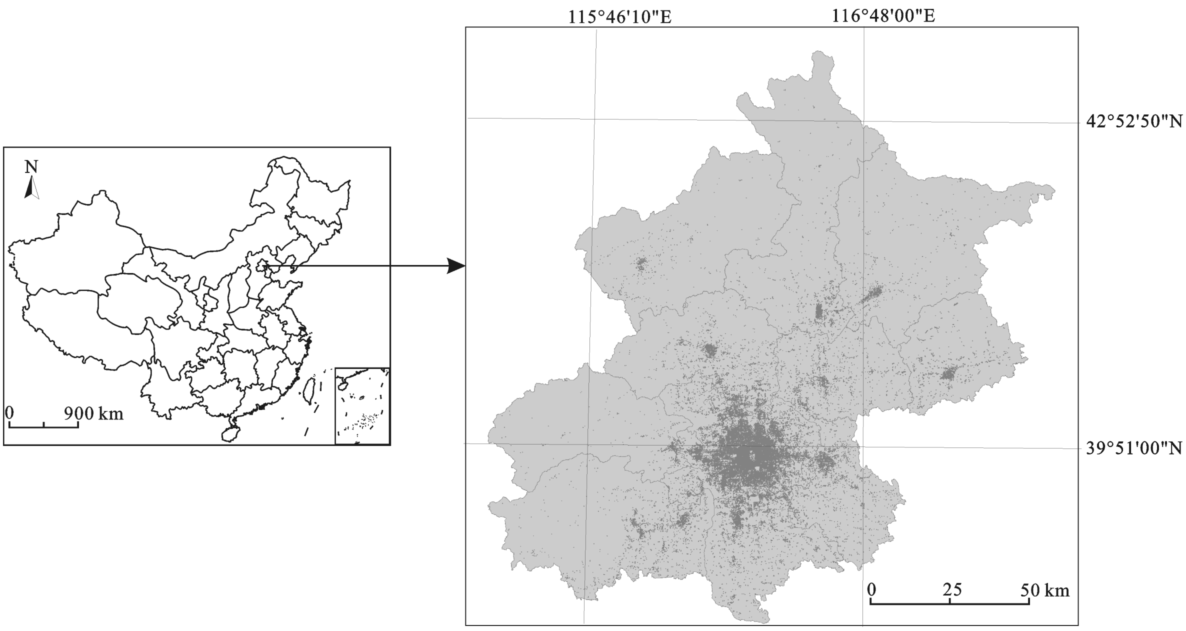


**Fig. 1** Spatial distribution of firm in Beijing

**Table 1** Categories of industries and number of firms

| Category | | Sector | Industrial type | Number of firms |
|---|---|---|---|---|
| Service industries | Business Service | Enterprises management service; law service; consulting and accounting service | Producer service | 59 399 |
| | Finance Service | Banking; security and commodity brokers; insurance; other finance activities | Producer service | 7059 |
| | Electronic Information Service | Computer services; communication; software | High-tech service | 13 038 |
| | Retail | Retail | Personal service | 44571 |
| Manufacturing industries | Computer and Communication Equipment | Computer and communication equipment | Knowledge-intensive manufacturing | 3987 |
| | Equipment Manufacturing | Transportation equipment; industrial machinery and equipment; special industry machinery | Equipment manufacturing | 13 122 |
| | Apparel and Other Textile | Apparel and other textile | Labor-intensive manufacturing | 5697 |
| | Raw Material Industry | Non-ferrous metal processing; petroleum processing; stone, clay, and glass products; chemicals and allied products | Capital-intensive manufacturing | 6612 |

Western countries. Furthermore, related sectors within the same branch tend to follow the similar spatial pattern, so our research is mainly based on 1-digit industries (Duranton and Overman, 2005). There is a huge difference in the number of firms between service and manufacturing industries. On average, each type of service industry contains 31 017 firms, whereas the figure is 7355 for manufacturing industries.

## 2.2 Methodology

### *2.2.1 Kernel estimates of K-density*

We mainly follow Duranton and Overman's method to estimate the spatial distribution of each industry. Supposing an industry $A$ with $n$ firms, we first compute the $n(n-1)/2$ unique bilateral distances between all pairs of the firms in that industry. Then we estimate the density distribution of these bilateral distances between the firms within the industry. For the industry $A$ with $n$ firms, the estimator of the density of bilateral distances at any point $d$ is:

$$\hat{K}(d) = \frac{1}{n(n-1)h} \sum_{i=1}^{n-1} \sum_{j=i+1}^{n} f\left(\frac{d - d_{i,j}}{h}\right) \quad (1)$$

where $d_{i,j}$ is the Euclidean distance between firms $i$ and

$j$. Gaussian kernel is employed to smooth the distribution. The bandwidth $h$ is set as Silverman (1986) stated

$$h = 0.9An^{-1/5}$$

where $A$ = min (standard deviation, interquartile range/1.34); $n$ is the quantity of firms.

But contrary to the work of Duranton and Overman with a small number of firms for each industry, the number is huge for most of industries in our investigation. For example, there are nearly 59 399 firms in Business Service, which means that the calculation the distance of all pairs of the firms will produce a matrix of 59 399 rows and 59 399 columns. The processing of such a big amount of data requires a computer with strong calculation capacity, which is exactly one significant weakness in the distance-based approaches (Mitchell, 2005). In practice, the calculating and processing of 8000 firms in one industry is quite difficult for most computers. Therefore, we have to rely on Monte Carlo methods to fit the spatial distribution for these industries. For each industry, we sample 5000 firms in turn and run 1000 simulations.

#### *2.2.2 Choice of a reference distribution*

Similar to Duranton and Overman's work, we also need to define a relevant reference distribution to which the K-densities of industries should be compared. Duranton and Overman mentioned that not all places in the whole space are suitable for the industrial locations, especially for manufacturing industries, due to the restrictions of zoning and planning. To control the overall tendency of spatial agglomeration, they defined the set of possible industrial locations as the whole set of locations where a firm currently locates, regardless of the industry it belongs to. This benchmark may be reasonable at the country level. Thus Barlet *et al.* (2013) adopted the same benchmark for the analysis of the industrial spatial distribution in France. However, the benchmark set by Duranton and Overman is obvious problematic at the city level. This is because there are usually two types of land use for economic activities-the industrial land and service land in the urban area. Some regulations that the local government makes ban a manufacturing firm locating on the service land and vice versa. Furthermore, there is a significant difference of the spatial distribution between service and manufacturing industries, as shown in Fig. 2. Due to the absolutely dominant number of service firms, the whole spatial pattern of all industries is apparently close to the service's pattern in Beijing. If we take the spatial distribution of all existing firms as the benchmark, the spatial agglomeration of manufacturing will be underestimated, whereas service is overestimated. Therefore, in this research we set two benchmarks for manufacturing and service industries respectively to test Beijing's industrial spatial agglomeration.

Correspondingly, we have four confidence intervals. Following Duranton and Overman's study, for each kilometer in this interval we rank our simulations in ascending order and select the 5-th and 95-th percentile to obtain a lower 5% and an upper 5% confidence interval for service and manufacturing industry. For the service industry $A$, when its estimator of K-density is more than the upper 95% confidence interval of service industry at the distance $d$, this industry is deemed to exhibit agglomeration at this distance. When its estimator is less than the lower 5% confidence interval, the industry exhibits dispersion at this distance. Between the two confidence intervals, its spatial distribution is random. This classification way also works for manufacturing industries.

## 3 Comparative Analysis of Spatial Patterns Among Various Types of Industries

Generally, service industry has a higher degree of agglomeration but a more limited agglomerating scope than manufacturing industry does. The index of spatial agglomeration for service industry is more than 0.04, whereas around 0.02 for manufacturing industry. In terms of the overall tendency of agglomeration, the degree of service industry at first rapidly increases up to the peak at the distance of around 12 km and then falls sharply. This tune continues and becomes even lower than the degree of manufacturing industry after the distance reaches 21 km (Fig. 2). While manufacturing industry has a high plateau between 20 and 30 km, the high degree of agglomeration for service industry keeps only between 9 and 12 km. On the one hand, the monocentric urban structure of Beijing leads to this result. As we know, there is a central agglomeration in the inner city of Beijing where most of service firms concentrate, while most of manufacturing firms have migrated to the outskirt. Furthermore the layer distribution of manufacturing industry forms several manufacturing cluster

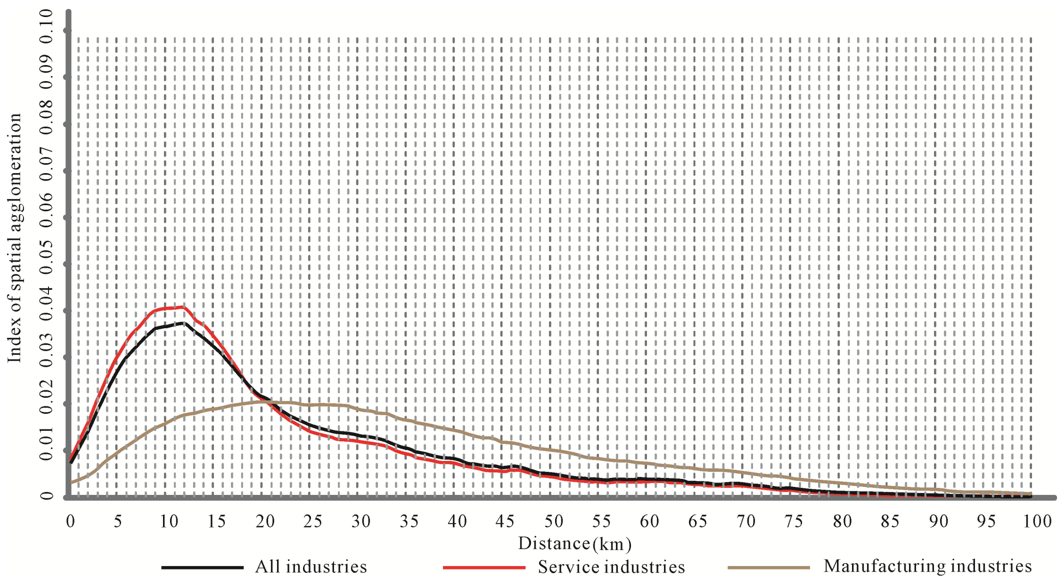


**Fig. 2** Industrial spatial pattern in Beijing

districts in different directions. Therefore, the distance between service firms is generally less than manufacturing. On the other hand, for the industrial development of other cities, it is the rule that the spatial scope of service industry clustering is less than that of the manufacturing (Table 2).

### 3.1 Comparison among service industries

The feature that four types of service industries have in common is the peak agglomerating distance—at around 9 km. Since the peak agglomerating distance is the most popular distance maintaining between firms, the scale of service agglomeration districts is around 9 km, regardless of the type of the industry. The concentration of service firms from different sectors inside the 4th ring road confirms this finding (Fig. 3). However, the discrepancies among these industries are apparent in other characteristics of the spatial pattern. Clearly, Electronic Information Service has the highest degree of spatial agglomeration (more than 0.05), followed by Business Service and Retail, and the agglomeration degree of Finance is lowest (Fig. 4). The distribution of firms also shows this point. There is merely one large cluster of Electronic Information Service in *Zhongguancun* Science Park (Fig. 3c). A large number of firms are located in this district, while few in other areas. The result is different from previous studies, which concludes that the agglomeration degree of Finance Service, as a producer service, should always be higher than that of Retail, which is a personal service. We argue that the unique spatial structure of Beijing would be the reason. There are two major finance clusters (CBD and Finance Street) in Beijing which are placed on the east and west side of *Tiananmen Square* respectively (Fig. 3a). The former hosts a large number of foreign banks and offices, and the latter hosts nearly all of the headquarters of major state-owned banks and financial regulators. Indeed, the peak agglomerating distance of Finance is at 8.5 km which is the same as the distance between CBD and Finance Street.

For Electronic Information Service and Business Service, a clear spatial agglomeration is detected at the distance of less than 15 km and less than 14 km respectively, while Finance Service and Retail exhibit only slight spatial agglomeration in urban space. Besides that, the agglomeration degrees of Electronic Information Service and Business Service are higher than mentioned above. Therefore, Electronic Information Service and Business Service probably form some specialized industrial districts in Beijing, while Finance Service and Retail need to co-agglomerate with other service industries to a large extent.

However, the figures reveal some important characteristics about Finance Service and Retail. For Finance Service, the spatial agglomerations are detected at two extreme distances (less than 3 km and more than 47 km). It is clear that there is more than one finance cluster existing in Beijing. However, the large interval between these two distances indicates most finance clusters are far away from the main service cluster, and that

that they locate in the periphery of metropolitan area. The picture of industrial distribution shows there are some finance clusters in suburb counties such as Huairou (Fig. 3a). Furthermore, the unclear agglomeration at a short distance manifests each finance cluster is relative small with low degree of specialization. For Retail, the distance of spatial agglomeration is unique. Retail firms are dispersed at short distances, but slightly clustered at higher levels of distances. The finding confirms that Retail needs a threshold distance to serve local market, so a Retail firm should keep a certain distance from other firms. However, the tendency of spatial distribution of Retail generally closes to the tendency of all service industries. To a large extent, such an industry demonstrates a random pattern in Beijing. The distribution of Retail consolidates the finding. Several Retail clusters scatter in the inner city (Fig. 3d).

### 3.2 Comparison among manufacturing industries

On the contrary to service industries, the difference in peak agglomerating distance is more significant than the difference in the degree of agglomeration among manufacturing industries. This fact suggests us to focus on the discrepancy of agglomeration scale (Fig. 5). Computer and Communication Equipment is an exception. While the extent of the spatial agglomeration of Computer and Communication Equipment is significantly high (the up to 0.038), even higher than Finance Service, other three industries have relatively low degrees of agglomeration and the gaps among them are slim (Fig. 6). Furthermore,

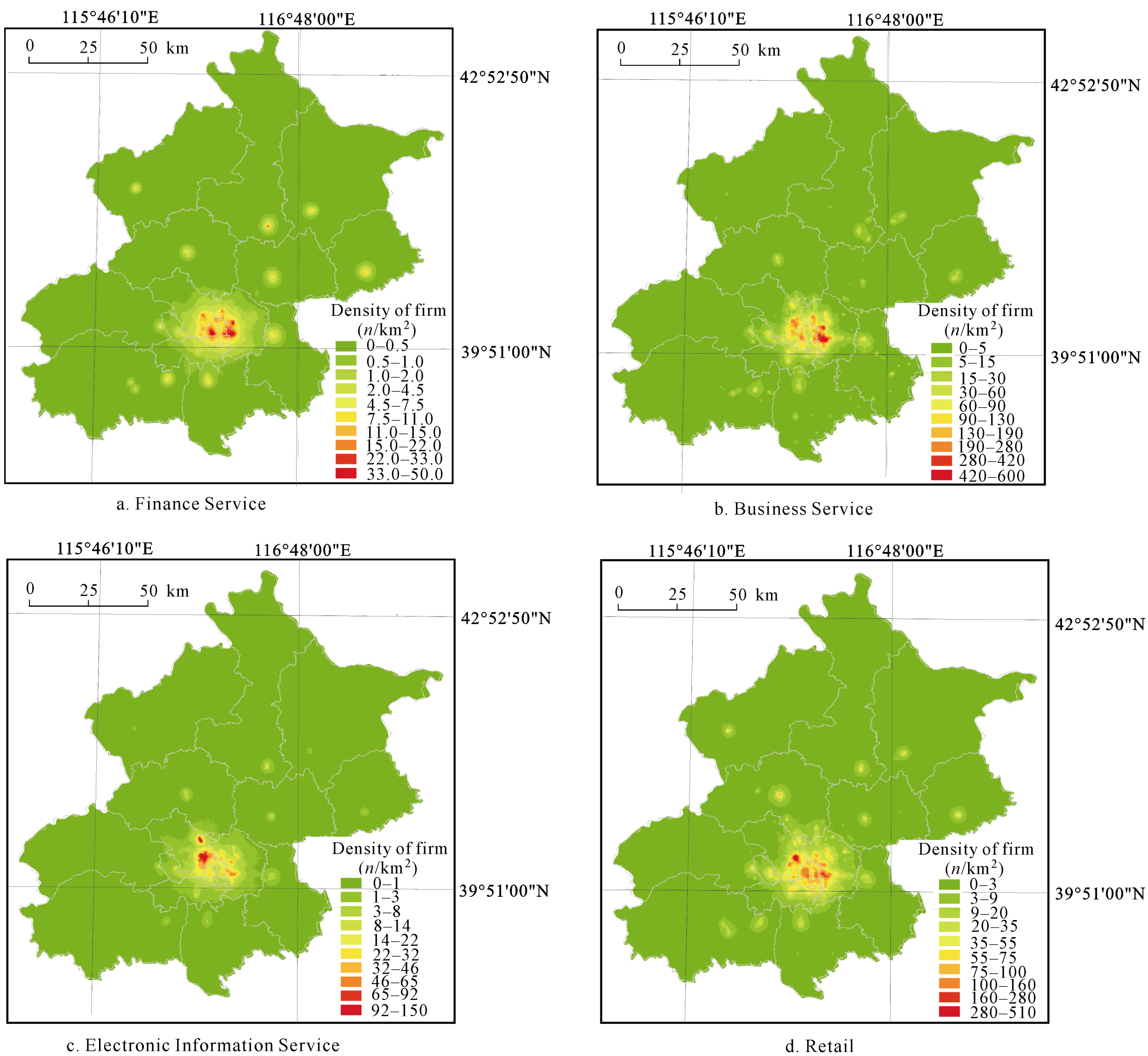


**Fig. 3** Spatial distribution of service industries ($n$ is the quantity of firms)

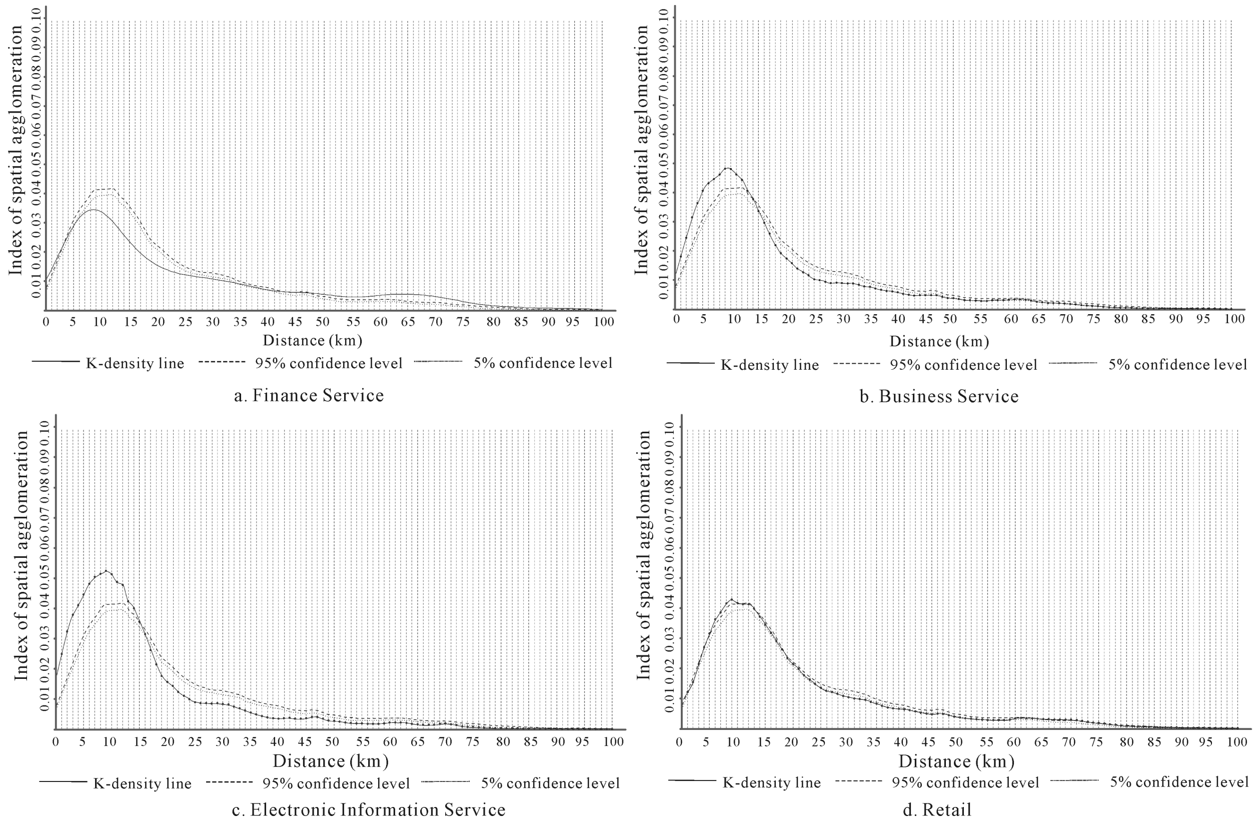


**Fig. 4** Spatial pattern of service industries

a large number of firms from Computer and Communication Equipment industry cluster in *Zhongguancun* Science Park and *Jiuxianqiao* Electronic City (Fig. 5a). Therefore, there is probably a high specialized industrial district in Beijing.

However, the agglomeration scales of various manufacturing industries are quite different. The peak agglomerating distance of Computer and Communication Equipment is the shortest, merely 11 km, and Apparel and Other Textile is slightly longer. Equipment Manufacturing and Raw Material Industry have the farthest distance, up to 30 km. Those results indicate the distances between most knowledge-intensive and labor-intensive manufacturing firms are shorter than between capital-intensive manufacturing firms. In other words, knowledge-intensive and labor-intensive industries are able to benefit more from the spatial proximity, such as spillover and forward and backward link, than capital industries do.

This conclusion has been consolidated by industries′ spatial patterns. Whereas Computer and Communication Equipment as well as Apparel and Other Textile have an obvious agglomeration pattern at the distance of less than 21 km and less than 12 km; the spatial clustering trend of Equipment Manufacturing and Raw Material Industry is ambiguous. It is clear that a textile cluster appears in the *Dahongmen*, despite that the spatial distribution of Apparel and Other Textile confirms the agglomeration degree of Apparel and Other Textile firms which is generally less than firms from Computer and Communication Equipment (Fig. 5c). Generally, the location of Equipment Manufacturing firms seems to be randomly scattered, despite that there is a marginal clustering at the distance of less than 23 km. For Raw Material Industry, the distribution pattern is dispersed. Although the manufacturing industry′s degree of agglomeration is slightly higher than the upper 5% confidence interval at the distance of more than 34 km, this distance is too long to benefit from agglomeration economy. The pictures show that firms from these two sectors scatter in urban space even thought there are many firms located in the inner city (Fig. 5b and Fig. 5d).

To sum up, High-tech services and manufacturing industries have the highest degree of agglomeration and specialization, due to the spillover from the spatial proximity. The spatial agglomeration degrees of

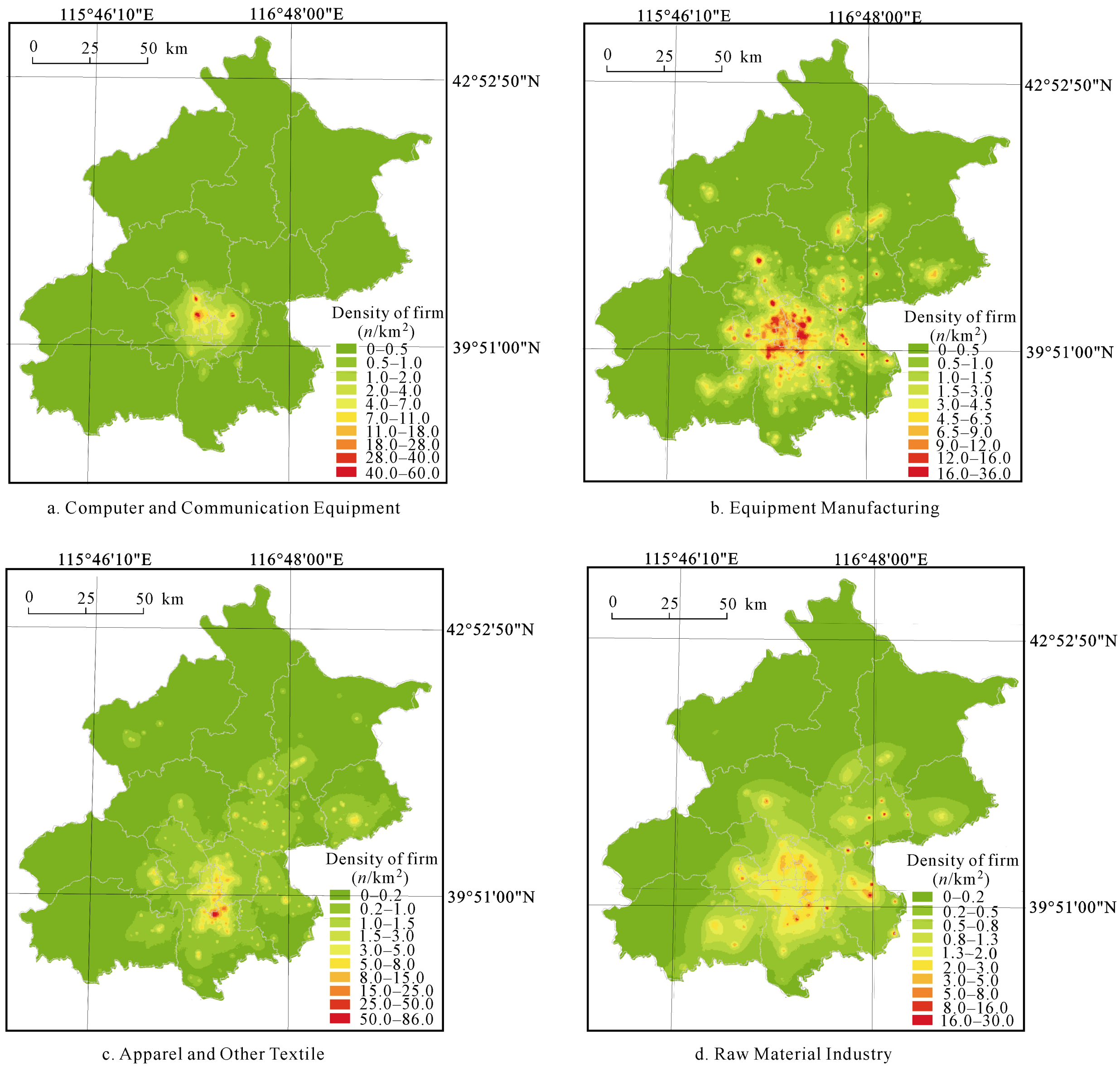


**Fig. 5** Spatial distribution of manufacturing industries ($n$ is the quantity of firms)

producer service and labor-intensive manufacturing industries are also relatively higher. The distribution pattern of person service firms and capital-intensive manufacturing industries in Beijing is randomly dispersed. However, Finance is an exception. Besides of the unique urban structure of Beijing, there is also another important reason that many branches of finance locates on the outskirts which mainly provide personal services.

## 4 Firm Size and Spatial Agglomeration

However, as we know, small and large firms tend to make different decision on location in spite of firms from the same sectors. Some empirical study has shown that the factors impacting on the location choice of large firms are different from small and median-sized firms. For example, the research from Carod and Antolín (2004) proves that large firms are based on objective factors, while smaller ones guide by more subjective reasons. More importantly, the choice of site from different size establishments, to a certain degree, reveals the industrial location in different development stages. Generally, as the establishments increase in size, they become more mature. The issue of size may be particularly crucial as firm-size distributions are much skewed in most industries. To explore the scale of localized establishments and the scope of agglomeration, we take the same analysis framework as we did with

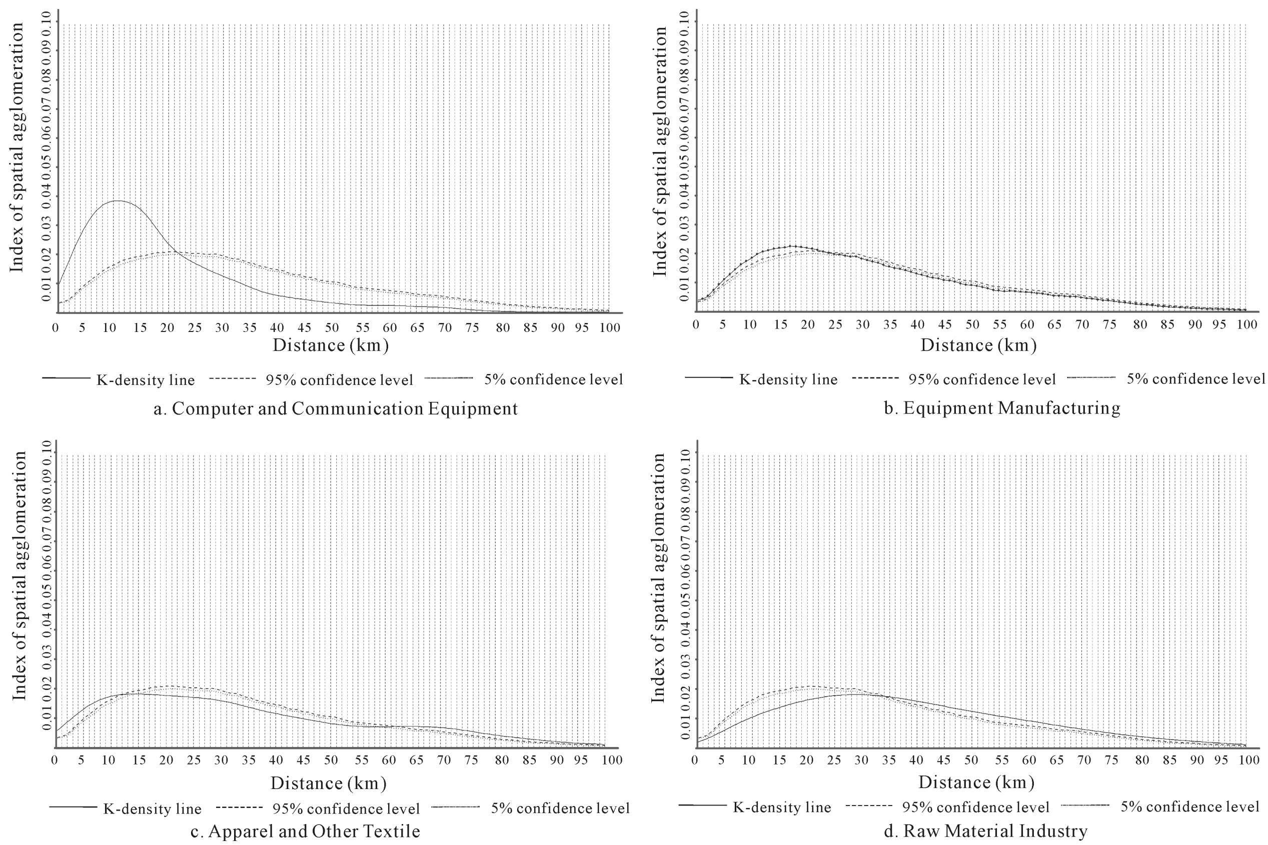


**Fig. 6** Spatial pattern of manufacturing industries

**Table 2** Test results of industrial spatial pattern

| Category | | Index of spatial agglomeration | Peak agglomerating distance (km) | Agglomerating scope (km) |
|---|---|---|---|---|
| Service industries | Business Service | 0.048 | 9.0 | 0–14 |
| | Finance | 0.034 | 8.5 | 0–3<br>≥47 |
| | Electronic Information Service | 0.053 | 9.0 | 0–15 |
| | Retail | 0.042 | 9.0 | 5–10<br>65–74 |
| Manufacturing industries | Computer and Communication Equipment | 0.038 | 11.0 | 0–21 |
| | Equipment Manufacturing | 0.022 | 17.0 | 0–23 |
| | Apparel and Other Textile | 0.018 | 13.5 | 0–12<br>≥63 |
| | Raw Material Industry | 0.018 | 30.0 | ≥34 |

the different sizes and types of firms.

Following the discussion on particular types of firms or particular sectoral definitions, this section deals with the influence of firm size on spatial agglomeration. According to the national standard issued by National Bureau of Statistics of the People′s Republic of China in 2011, the classification of firm size is based on the employment scale of firms. All firms are classified into three categories: small-sized, median-sized and large firms (Table 3).

**Table 3** Classification of firm size (person)

| Firm size | Business Service | Finance | Electronic Information Service | Retail | Computer and Communication Equipment | Equipment Manufacturing | Apparel and Other Textile | Raw Material Industry |
|---|---|---|---|---|---|---|---|---|
| Large | ≥300 | ≥300 | ≥300 | ≥300 | ≥1000 | ≥1000 | ≥1000 | ≥1000 |
| Median-sized | 100–300 | 100–300 | 100–300 | 50–300 | 300–1000 | 300–1000 | 300–1000 | 300–1000 |
| Small-sized | <100 | <100 | <100 | <50 | <300 | <300 | <300 | <300 |

For most service industries, along with the decrease of firm size, the degree of spatial agglomeration becomes lower. In other words, the large-size service firms are more likely to agglomerate together in Beijing. For Finance and Electronic Information Service, the agglomeration degree of large enterprises is significantly higher than the reference (the degrees are up to 0.06 and 0.07, respectively). However, there are differences between them. The agglomeration trend of median-sized finance enterprises is close to the trend of small ones and its agglomeration degree is low, while the spatial distribution of the median-sized enterprises of Electronic Information Service is similar to that of large ones. Moreover, although the agglomeration degree of large high-tech service firms is higher than the degree of large finance firms, the distance between large high-tech service firms is relatively greater (Fig. 7c). Long distance means there are more large-sized high-tech firms clustering in one region, but the clustering scope is larger than finance industry. There are two characteristics of Finance Industry unfolded by the Fig.7a. On one hand, although the general trend of spatial agglomeration is slightly unclear, the clustering of large- and median-sized firms is significant. Besides that, the distance between large firms is relatively shorter. These findings indicate that the large enterprises in Finance have clustered significantly in Beijing. On the other hand, the figure also shows that the estimators of median- and small-sized firms rather than large firms are significantly above the upper 5% confidence interval at the distance between 57 and 75 km. This fact means the clusters on the outskirts are composed of small and median-sized enterprises. However, an upward trend is detected after a sharp decline for large firms at the distance of between 35 and 40 km. This change may be a sign of the emergence of the clusters of large finance enterprise on the margin of urban area.

Like Finance, the agglomeration degree of large retail firms is also higher than that of small- and median-sized firms, but the agglomeration degree of large retail firms is the lowest in the service industries. For Retail, there are little differences in agglomeration trends among various firm sizes. Therefore, the spatial distribution of retail firms in Beijing is a random pattern, having nothing to do with firm sizes. Business Service is different from other service industries. The discrepancy across firm scales is obvious. The agglomeration degree of median-sized firm is the highest, the degree of small-sized firms is the lowest and the degree of large firms is in between. This result demonstrates that, for Business Service, agglomeration economy has more significant influence on median-sized enterprises than large firms.

For manufacturing industries, the agglomeration trend across firm scales is mixed. Most large manufacturing firms do not cluster more often in one region than small- and median-sized firms do, even though the agglomeration degree of large firms is the lowest in some manufacturing industries, such as Computer and Communication Equipment and Apparel and Other Textile (Fig. 8). For Computer and Communication Equipment, the degree of spatial agglomeration of large enterprises is notably lower than that of small- and median-sized firms, despite that the agglomeration trend of such firms is still above the reference of manufacturing industry at a certain distance. It is worth noting that small- and median-sized high-tech manufacturing firms are more likely to cluster and then form Marshallian industrial districts (Coe, 2001). For Apparel and Other Textile, the very flatten agglomeration trend of large enterprises indicates large firms are scattered randomly in the whole urban space. The distribution of Large- and median-sized firms are dispersed on industrial lands, while small-sized firms tend to cluster at a distance of less than 10 km. The distribution pattern implies that small textile firms need to cooperate with other firms.

For Equipment Manufacturing, large firms seem to cluster more frequently than small- and median-sized firms. Basically, the large equipment manufacturing firms cluster obviously at the distance of less than

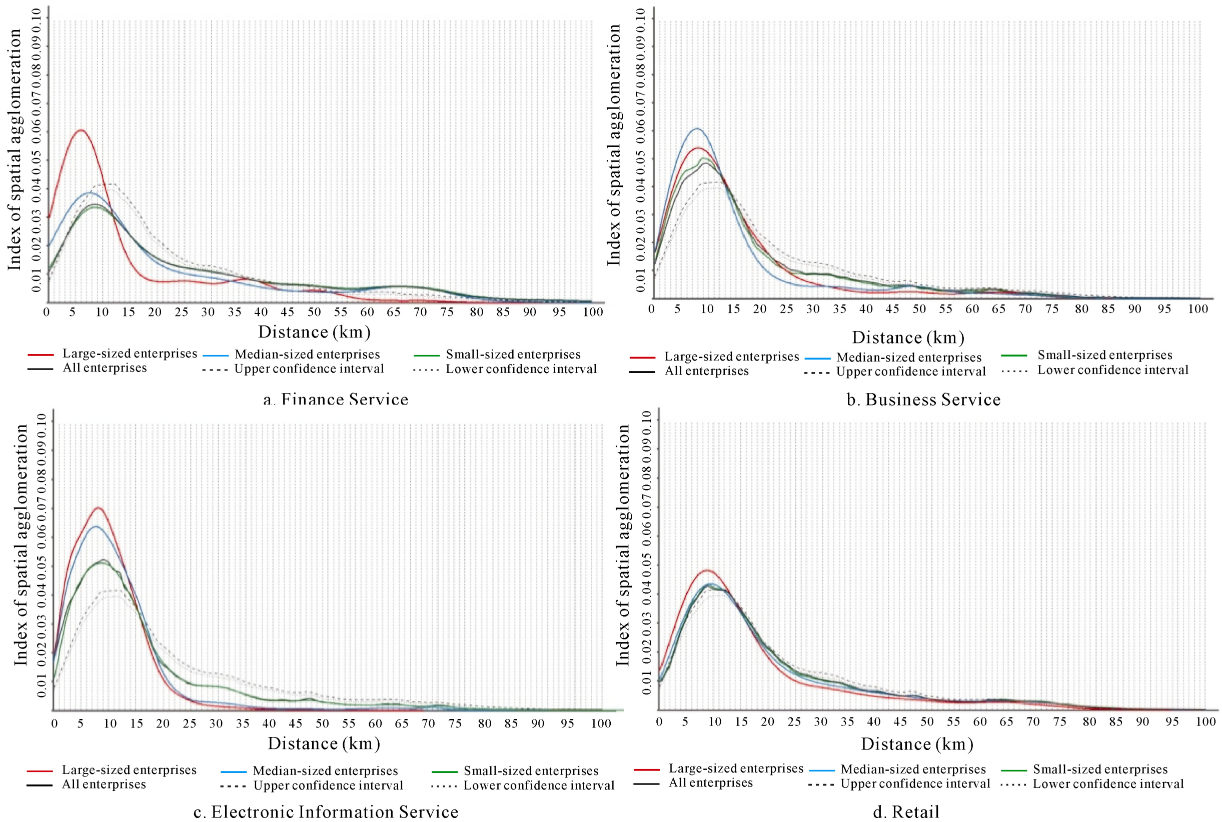


**Fig. 7** Spatial agglomeration tendency of service industries across firm sizes

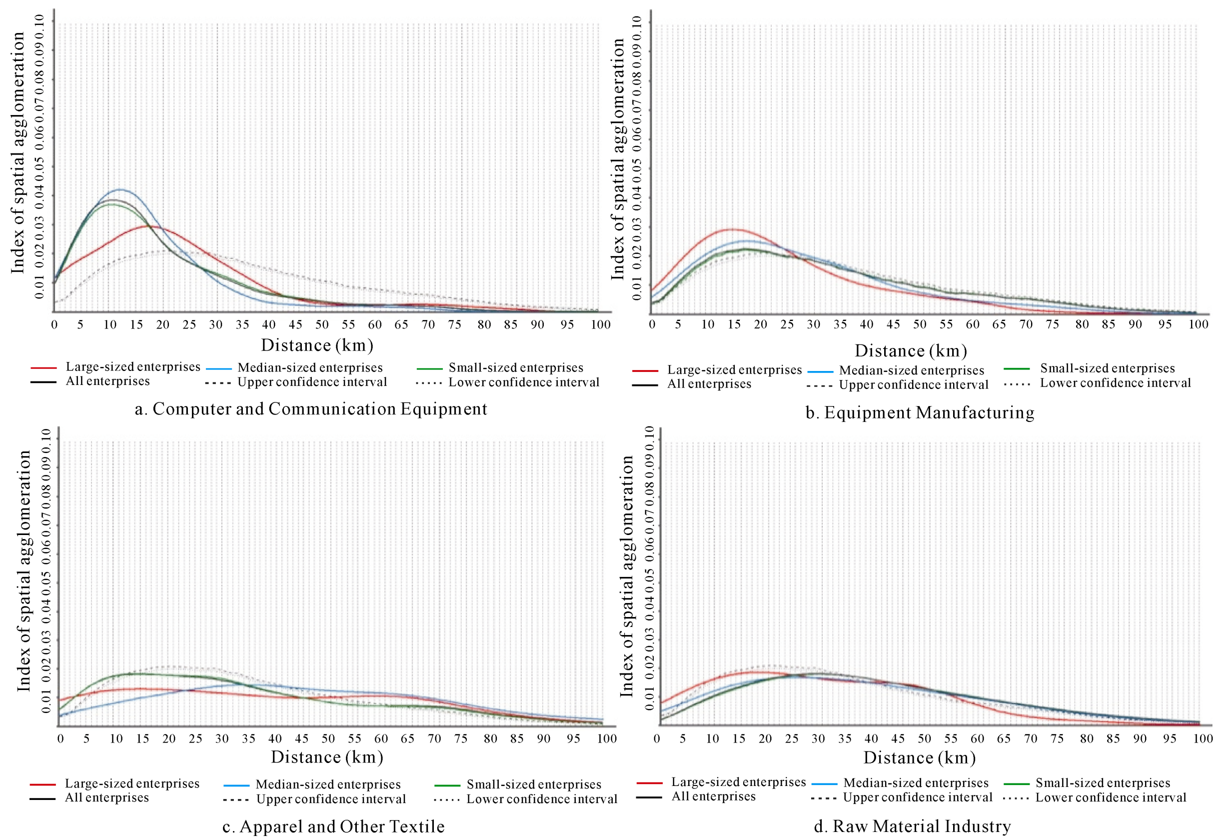


**Fig. 8** Spatial agglomeration tendency of manufacturing industries across firm sizes

20 km, and the agglomeration degree of large equipment manufacturing firms is almost the highest in manufacturing industries. In general, the agglomeration trend of Raw Material Industry across firm sizes is similar to that of Equipment Manufacturing, but has a more flatten shape. Most firms disperse in industrial space, except for some large firms slightly clustering at a short distance of less than 7 km. These findings of Equipment Manufacturing and Raw Material Industry reveal that industrial space of heavy industries in Beijing may be an annular pattern, and that large firms are located inside the ring and small- and median-sized firms distribute around them.

## 5 Conclusions

Spatial agglomeration is the most significant characteristic of the distribution of industries. From the perspective of economic geography, the spatial scale and scope area are as important as the agglomeration degree in the issue of industrial agglomeration. Using a distance-based approach, which considers space as continuous, this paper examines the differences among the spatial patterns of various industries and diverse firm sizes in Beijing. Unlike previous researches, we construct two sets of confidence intervals for service and manufacturing industries respectively to investigate the industrial spatial distribution at the city level. Our research shows that service industries have a relatively high extent but small scope of agglomeration, which is opposite to manufacturing industries. It means that the service industries is more concentrated the manufacturing industries. However the study in the national scale has an opposite conclusion.

However, our study further reveals that the agglomeration scales across manufacturing industries are greatly diverse. Instead, the scales of service clusters in Beijing uniformly stay at the distance of around 9 km. Although the research from Marcon and Puech (2003) also indicate that the scales of significant concentration of manufacturing industries are very different from 1 km to all distance, the peak agglomerating distance of manufacturing industries in Pairs is obviously less than that in Beijing.

It is no doubt that the spatial patterns between service industries and manufacturing industries are apparently different. For service industries, the spatial distribution of firms in Electronic Information Service and Business Service present a strong agglomeration pattern, while Finance performs a slight agglomeration at a short distance, and Retail enterprises distribute randomly in service space. With regard to manufacturing industries, Computer and Communication Equipment and Apparel and Other Textile cluster, Equipment Manufacturing places randomly, and Raw Material Industry exhibits dispersion. To sum up, producer service, high-tech industries and labor-intensive manufacturing industries are more likely to cluster, whereas personal service and capital-intensive industries tend to randomly place throughout the city.

Some important issues should be noted here. Firstly, the extent of agglomeration in high-tech industries is significantly above the reference system, and even higher than that in business-oriented services at the city level. This result manifests that the spillover of the co-location of firms is more important to knowledge-intensive industries and has more significant impact on their allocation than business-oriented services in the intra-urban area. Secondly, the spatial agglomerations of Finance at two extreme distances indicate a polycentric spatial structure in Beijing. Moreover, the finance clusters located on outskirts suburbs are composed of small- and median-sized enterprises. Although the estimators of Retail and Apparel and Other Textile are also above the reference system, it is not confident enough to judge there is a polycentric structure. Thirdly, the finding of Retail dispersing at short distances but clustering at long distances confirms the hypothesis of the threshold distance in central place theory. Lastly, government can influence the industrial spatial patterns fundamentally. For instance, local government has planned two finance agglomeration districts, which, to a large extent, contribute to the unclear agglomeration pattern of Finance in Beijing.

Firm sizes also highlight some significant characteristics of the industrial spatial pattern. Generally, the spatial agglomeration of service industries is driven by large establishments, whereas the spatial pattern of manufacturing industries is mixed. Specifically, the extent of agglomeration of large finance establishments is similar to that of large and median-sized high-tech service enterprises, despite that its whole agglomeration trend is unclear. Although large retail firms cluster more often than small- and median-sized firms, the whole distribution pattern still tends to be random. A slightly discrepancy among them is that median-sized business enterprises are more likely to cluster than large ones. For manufacturing industries, small- and median-sized plants in high-tech manufacturing and textile industries have a strong tendency to cluster, whereas in equipment manufacturing and raw materials large plants are more likely to agglomerate. These findings further confirm the conclusions of previous investigations to a certain extent.

## References


Alfaro L, Chen M, 2014. The global agglomeration of multinational firms. *Journal of International Economics*, 94(2): 263–276. doi: 10.1016/j.jinteco.2014.09.001

Anselin L, 1995. Local indicators of spatial association—LISA. *Geographical Analysis*, 27(2): 93–115. doi: 10.1111/j.1538-4632.1995.tb00338.x

Arbia G, Espa G, Quah D, 2008. A class of spatial econometric methods in the empirical analysis of clusters of firms in the space. *Empirical Economics*, 34(1): 81–103. doi: 10.1007/s00181-007-0154-1

Barlet M, Briant A, Crusson L, 2013. Location patterns of service industries in France: a distance-based approach. *Regional Science and Urban Economics*, 43(2): 338–351. doi: 10.1080/00343400500151806

Bertinelli L, Decrop J, 2005. Geographical agglomeration: Ellison and Glaeser's index applied to the case of Belgian manufacturing industry. *Regional Studies*, 39(5): 567–583. doi: 10.1080/00343400500151806

Braunerhjelm P, Borgman B, 2004. Geographical concentration, entrepreneurship and regional growth: evidence from regional data in Sweden, 1975–1999. *Regional Studies*, 38(8): 929–947. doi: 10.1080/0034340042000280947

Briant A, Combes P P, Lafourcade M, 2010. Dots to boxes: do the size and shape of spatial units jeopardize economic geography estimations? *Journal of Urban Economics*, 67(3): 287–302. doi: 10.1080/0034340042000280947

Brülhart M, Sbergami F, 2009. Agglomeration and growth: Cross-country evidence. *Journal of Urban Economics*, 65(1): 48–63. doi: 10.1016/j.jue.2008.08.003

Carlos G R, José A, Álvarez L *et al*., 2013. Calculating intraurban agglomeration of economic units with planar and network K-functions: a comparative analysis. *Urban Geography*, 34: 2, 261–286. doi: 10.1080/02723638.2013.778655

Carod J M A, Antolín M C M, 2004. Firm size and geographical aggregation: an empirical appraisal in industrial location. *Small Business Economics*, 22(3–4): 299–312. doi: 10.1023/B:SBEJ.0000022216.09083.76

Chen Hongxia, Li Guoping, 2011. Empirical study on effect of industrial structure change on regional economic growth of Beijing-Tianjin-Hebei Metropolitan Region. *Chinese Geographical Science*, 21(6): 708–714. doi: 10.1007/s11769-011-0478-9

Ciccone A, 2002. Agglomeration effects in Europe. *European Economic Review*, 46(2): 213–227. doi: 10.1016/S0014-2921(00)00099-4

Clark G L, Gertler M S, Feldman M P, 2003. *The Oxford Handbook of Economic Geography*. Oxford: Oxford University Press.

Coe N M, 2001. A hybrid agglomeration? The development of a satellite-Marshallian industrial district in Vancouver's film industry. *Urban Studies*, 38(10): 1753–1775. doi: 10.1080/00420980120084840

Coe N M, Kelly P F, Yeung H W C, 2007. *Economic Geography: A Contemporary Introduction*. Oxford: Blackwell.

Devereux M P, Griffith R, Simpson H, 2004. The geographic distribution of production activity in the UK. *Regional Science and Urban Economics*, 34(5): 533–564. doi: 10.1016/S0166-0462(03)00073-5

Duranton G, Overman H G, 2005. Testing for localization using micro-geographic data. *Review of Economic Studies*, 72(4): 1077–1106. doi: 10.1111/0034-6527.00362

Ellison G, Glaeser E L, 1997. Geographic concentration in US manufacturing industries: a dartboard approach. *Journal of Political Economy*, 105(5): 889–927. doi: 10.1086/262098

Ellison G, Glaeser E L, Kerr W, 2010. What causes industry agglomeration? Evidence from coagglomeration patterns. *American Economic Review*, 100(3): 1195–1213. doi: 10.1257/aer.100.3.1195

Fischer M M, Getis A, 2009. *Handbook of Applied Spatial Analysis: Software Tools, Methods and Applications*. Berlin: Springer Science & Business Media.

Fujita M, 1988. A monopolistic competition model of spatial agglomeration: differentiated product approach. *Regional Science and Urban Economics*, 18(1): 87–124. doi: 10.1016/0166-0462(88)90007-5

Guillain R, Le Gallo J, 2010. Agglomeration and dispersion of economic activities in and around Paris: an exploratory spatial data analysis. *Environment and planning B*, 37(6): 961–981. doi: 10.1068/b35038

Goetz S J, Rupasingha A, 2002. High-tech firm clustering: implications for rural areas. *American Journal of Agricultural Economics*, 84(5): 1229–1236. doi: 10.1111/1467-8276.00383

Glaeser E L, Kallal H D, Scheinkman J A *et al*., 1992. Growth in cities. *Journal of Political Economy*, 100(6): 1126–1152.

Haining R P, 2003. *Spatial Data Analysis*. Cambridge: Cambridge University Press.

Henderson J V, 2003. Marshall′s scale economies. *Journal of Urban Economics*, 53(1): 1–28. doi: 10.1016/S0094-1190(02)00505-3

HUallachain B O, Leslie T F, 2009. Postindustrial manufacturing in a Sunbelt Metropolis: where are factories located in Phoenix? *Urban Geography*, 30(8): 898–926. doi: 10.2747/0272-3638.30.8.898

Krugman P, 1991a. Increasing returns and economic geography. *Journal of Political Economy*, 99(3): 483–499.

Krugman P, 1991b. *Geography and Trade*. Cambridge: MIT press.

Lin H L, Li H Y, Yang C H, 2011. Agglomeration and productivity: firm-level evidence from China′s textile industry. *China Economic Review*, 22(3): 313–329. doi: 10.1016/j.chieco.2011.03.003

Logan J R, Spielman S, Xu H *et al*., 2011. Identifying and bounding ethnic neighborhoods. *Urban Geography*, 32(3): 334–359. doi: 10.2747/0272-3638.32.3.334

Marcon E, Puech F, 2003. Evaluating the geographic concentration of industries using distance-based methods. *Journal of Economic Geography*, 3(4): 409–428. doi: 10.1093/jeg/lbg016

Marcon E, Puech F, 2010. Measures of the geographic concentration of industries: improving distance-based methods. *Journal of Economic Geography*, 10(8): 745–762. doi: 10.1093/jeg/lbp056

Marshall A, 1890. *Principles of Economics*. London: Macmillan and Company, limited.

Mitchell A, 2005. *The ESRI Guide to GIS Analysis*. Redlands, CA: ESRI Press.

Morphet C S, 1997. A statistical method for the identification of spatial clusters. *Environment and Planning A*, 29(6): 1039–1055. doi: 10.1068/a291039

Ripley B D, 1976. The second-order analysis of stationary point processes. *Journal of Applied Probability*, 13(2): 255–266.

Ripley B D, 1977. Modelling Spatial Patterns. *Journal of the Royal Statistical Society B*, 39(2): 172–212.

Silverman B W, 1986. Density estimation for statistics and data analysis. *New York*: *Chapman and Hall*.

Van Oort F G, Atzema O A L C, 2004. On the conceptualization of agglomeration economies: the case of new firm formation in the Dutch ICT sector. *The Annals of Regional Science*, 38(2): 263–290. doi: 10.1007/s00168-004-0195-8

Venables A J, 1996. Equilibrium locations of vertically linked industries. *International Economic Review*, 37(2): 341–359.

Yang D Y R, Wang H K, 2008. Dilemmas of local governance under the development zone fever in China: a case study of the Suzhou region. *Urban Studies*, 45(5–6): 1037–1054. doi: 10.1177/0042098008089852

Yeh A G O, Li X, 1999. Economic development and agricultural land loss in the Pearl River Delta, China. *Habitat international*, 23(3): 373–390. doi: 10.1016/S0197-3975(99)00013-2

Zhang Jingqiu, Chen Yelong, 2011. Industrial distribution and clusters of urban office space in Beijing. *Acta Geoprahica Sinca*, 66(10): 1299–1308. (in Chinese)

Zhang Xiaoping, Sun Lei, 2012. Manufacture restructuring and main Determinants in Beijing. *Acta Geopraphica Sinca*, 67(10): 1308–1316. (in Chinese)

Zhou Shangyi, Ji Limei, 2009. Commercial space succession in old city of Beijing-case of survey line of inner city in Beijing from 1996 to 2006. *Scienta Geographica Sinica*, 29(4): 493–499. (in Chinese)