Impact of the Built Environment on the Spatial Heterogeneity of Regional Innovation Productivity: Evidence from the Pearl River Delta, China

Article *in* Chinese Geographical Science · February 2021

DOI: 10.1007/s11769-021-1198-4

5 authors, including:

Kangmin wu
Guangzhou Institute of Geography, Guangdong Academy of Sciences

Chin. Geogra. Sci.
https://doi.org/10.1007/s11769-021-1198-4

Springer Science Press
www.springerlink.com/content/1002-0063

Impact of the Built Environment on the Spatial Heterogeneity of Regional Innovation Productivity: Evidence from the Pearl River Delta, China

WU Kangmin[1, 2, 3], WANG Yang[1, 2, 3], ZHANG Hong'ou[1, 2, 3], LIU Yi[1, 2, 4], YE Yuyao[1, 2, 3]

(1. *Key Lab of Guangdong for Utilization of Remote Sensing and Geographical Information System*, *Guangdong Open Laboratory of Geospatial Information Technology and Application*, *Guangzhou Institute of Geography*, *Guangdong Academy of Sciences*, *Guangzhou* 510070, *China*; 2. *Institute of Strategy Research for Guangdong*, *Hong Kong and Macao Greater Bay Area*, *Guangzhou* 510070, *China*; 3. *Southern Marine Science and Engineering Guangdong Laboratory* (*Guangzhou*), *Guangzhou* 511458, *China*; 4. *Key Laboratory of Regional Sustainable Development Modeling*, *Institute of Geographic Sciences and Natural Resources Research*, *Chinese Academy of Sciences*, *Beijing* 100101, *China*)

Abstract: With the global economy increasingly dependent on innovation, urban discourse has shifted to consider what kinds of spatial designs may best nurture innovation. We examined the relationship between the built environment and the spatial heterogeneity of regional innovation productivity (RIP) using the example of China's Pearl River Delta (PRD). Based on a spatial database of 522 546 patent data from 2017, this study proposed an innovation-based built environment framework with the following five aspects: healthy environment, daily interaction, mixed land use, commuting convenience, and technology atmosphere. Combining negative binomial regression and Geodetector to examine the impact of the built environment on RIP, the results show that the spatial distribution of innovation productivity in the PRD region is extremely uneven. The negative binomial regression results show that the built environment has a significant impact on the spatial differentiation of RIP, and, specifically, that healthy environment, mixed land use, commuting convenience, and technology atmosphere all demonstrate significant positive impacts. Meanwhile, the Geodetector results show that the built environment factor impacts the spatial heterogeneity of RIP to varying degrees, with technology atmosphere demonstrating the greatest impact intensity. We conclude that as regional development discourse shifts focus to the knowledge and innovation economy, the innovation-oriented design and updating of built environments will become extremely important to policymakers.

Keywords: built environment; innovation productivity; patent; spatial heterogeneity; Pearl River Delta

Citation: WU Kangmin, WANG Yang, ZHANG Hong'ou, LIU Yi, YE Yuyao. Impact of the Built Environment on the Spatial Heterogeneity of Regional Innovation Productivity: Evidence from the Pearl River Delta, China. *Chinese Geographical Science*. https://doi.org/10.1007/s11769-021-1198-4

1 Introduction

In the past few decades, the global economy has gradually shifted from the neoclassical industrial production paradigm to the knowledge-based innovation paradigm. Innovation, technology, and creativity have become in-

Received date: 2020-07-10; accepted date: 2020-11-08

Foundation item: Under the auspices of National Natural Science Foundation of China (No. 41871150), GDAS' Project of Science and Technology Development (No. 2021GDASYL-20210103004), National Key Research and Development Program (No. 2019YFB2103-101), Special Construction Project of Guangdong-Hong Kong-Macao Greater Bay Area Strategic Research Institute (No. 2020GDASYL-20200201001), Key Special Project for Introduced Talents Team of Southern Marine Science and Engineering Guangdong Laboratory (Guangzhou) (No. GML2019ZD0301)

Corresponding author: WANG Yang. E-mail: wyxkwy@163.com

tegral to the mainstream discourse regarding economic development (Capello and Lenzi, 2016; Esmaeilpoorarabi et al., 2018b; Lv et al., 2019). In an ever-changing global environment, innovation productivity has been widely recognized as an important source of regional competitive advantage (Crossan and Apaydin, 2010; Capello, 2017; Chen et al., 2017). As a major manufacturing country, China has been trying to transform its role in the global production network from an assembler to a high value-added technology-intensive producer (Yang, 2014).

The relationship between innovation and location has received substantial attention in research. The mechanism of innovation agglomeration and location choice involves two aspects: the production of knowledge and the choice of location of the innovation activities. Studies have identified two major mechanisms of innovation production and aggregation, namely, agglomeration and diversity (Adler et al., 2019; Zhang and Wu, 2019).

The agglomeration paradigm emphasizes the significant role of proximity, co-location, knowledge spillover, and agglomeration externalities in innovation (Marshall, 1890). More concepts, such as knowledge, cognitive, social, institutional, and organizational proximity (Boschma, 2005; Rammer et al., 2019), have further been proposed to explain the emergence of innovation. The diversity paradigm emphasizes the impact of heterogeneity on innovation, highlighting the knowledge spillover and urban buzz are brought about by diversity (Capello and Lenzi, 2018). The impact of cultural or social diversity, racial diversity, sexual diversity, gender diversity, and other factors on the aggregation of creative class and RIP have been examined in literatures (Florida, 2002; Florida et al., 2008; Qian, 2013; Bereitschaft and Cammack, 2015; Ozgen et al., 2017; Wixe, 2018).

In recent years, innovation research has begun to focus on the impact of place quality on high-quality labor agglomeration and innovation productivity. Place quality is the physical response of the urban development to the new socio-economic paradigm. It focuses on knowledge-based and innovation-based urban development (Esmaeilpoorarabi et al., 2018a) and on the provision of a high-quality living environment for knowledge-based professionals to create a pool of talent and innovation, thereby creating a spatial differentiation of innovation capacity. This concept established a connection between innovation clusters and the urban environment on a finer-grained level (Van Winden et al., 2012; Esmaeilpoorarabi et al., 2018a; 2018b; 2018c).

In past studies, the built environment factor has been incorporated into the discussion on innovation location. Accessibility (Ewing et al., 2016), urban amenity (Li et al., 2019), urban form (Hamidi and Zandiatashbar, 2018; Hamidi et al., 2019), mixed use, and urban density (Carlino et al., 2007) have been partly incorporated into the discussion framework of innovation location. Li et al. (2019) found that urban amenities attract high-quality professionals, and hence, they significantly influence business location decisions and employment concentration. Hamidi et al. (2019) examined the relationship between urban compactness and start-ups and regional innovation capacity and found that compact development is more conducive to the development of local innovation capacity. Esmaeilpoorarabi et al. (2018a) analyzed the spatial structural characteristics of innovation districts by constructing a conceptual framework of place quality with five aspects comprising form, context, function, image, and ambience; the author concluded that an effective integration of innovation districts into cities and a regard for public needs are more likely to create a vibrant environment that attracts and retains talent and investment. Zandiatashbar and Hamidi (2018) found that transit service quality and walkability contribute toward forming a robust local knowledge economy through the influence of knowledge intensive business services and the creative class. Wood and Dovey (2015) found that a compact and diverse development model facilitates face-to-face contact with urban buzz, which significantly increases local innovation productivity. Spencer (2015) empirically analyzed the differences in distribution preference between creative and high-tech industries from the perspective of evolutionary economic geography and found that knowledge-intensive firms tend to located in high-density, mixed-use neighborhoods of city centers.

However, we also note that the built environment is often partially conceptualized as part of the location conditions and is incorporated as an independent factor into the analysis framework of agglomeration, diversity, or place quality in the literature on location and innovation. The literature on innovation location lacks systematic organization and conceptualization of the built environment. Compared to the mere concepts of accessibility and urban service facilities, the built environment is a broader concept including infrastructure conditions, local technological innovation environment, environmental health quality, and so on. Meanwhile, although existing regression studies reveal the relationship between built environment factors and innovation, these studies neglect the spatial dimension. Accordingly, the impact of the built environment on the spatial heterogeneity of regional innovation productivity remains underexplored.

What is the relationship between the built environment and RIP? How strong is its impact on the spatial heterogeneity of RIP? Is there heterogeneity in the intensity of impact among the built environment factors? Although some studies have theoretically described these relationships, there is hardly any research that systematically conceptualizes the built environment and obtains empirical evidence from the spatial dimension.

This study aims to find out how the built environment affects the spatial heterogeneity of RIP. We chose the Pearl River Delta (PRD) in China as a case study and attempted to conceptualize the built environment systematically from the perspective of innovation. We went one step further with the regression analysis method by using Geodetector to measure the degree to which built environment factors impact the spatial heterogeneity of RIP.

2 An Innovation-based Built Environment

2.1 Innovation productivity

Drawing on the concept of national innovation capacity, we define RIP as the ability of a region to produce and commercialize new technologies (Furman et al., 2002; Proksch et al., 2017). Rooted in the growth theory developed in the 1950s and later discussions about long-run growth and competitive advantages (Porter, 1998; Freeman, 2002), these studies point toward innovation, science, and technology as the cornerstones of economic growth. Innovation productivity is one of the main drivers of long-term regional economic growth (Proksch et al., 2017). The utilization of high-tech development strategies and the promotion of regional innovation capacity to enhance regional competitiveness (Fagerberg and Srholec, 2008) constitute an important policy direction at both the regional and national levels.

Widely accepted agents for measuring innovation performance include number of patents, innovation awards, investment in R&D, and academic papers (Furman et al., 2002; Carlino et al., 2007; Ma et al., 2015; Duan et al., 2016; Hamidi and Zandiatashbar, 2018; Li and Phelps, 2018; Hamidi et al., 2019). However, there are various drawbacks to these indicative proxy data, such as the fact that investment in R&D may favor large firms and overlook the innovation of small businesses (Hamidi et al., 2019). Academic papers may focus more on academic innovation. These problems have been noted in past studies (Carlino et al., 2007). Despite these problems, patents, innovation inputs, awards, and academic papers, among others, still function as important markers of innovation input and output. Of these innovation output markers, the most widely used indicator to measure innovation productivity is patent data (Hamidi et al., 2019).

2.2 Built environment: concepts and indicators

The built environment comprises human-made physical environments, including various basic amenities (roads, urban amenities, recreational facilities, *etc*.) (Zhang and Yin, 2019). The concept of 'built environment' has different meanings at different scales (Yang and Zhou, 2020). One type of research explores the role of the built environment by examining the relationship between the urban development characteristics of administrative districts (county, city, and metropolitan area) and certain research subjects. Current scholars have widely used this perspective to examine the relationship among built environment characteristics and the obesity epidemic (Zhang and Yin, 2019; Yang and Zhou, 2020), body mass (Sun and Yin, 2018), health, safety (Casares Blanco et al., 2019), and upward mobility (Hamidi and Ewing, 2015). Another type of research at a microscale has shifted the research perspective to communities or an analysis of a specific site. This type of research is more concerned with the impact of a specific environmental field on the research subject, as it aims to understand the mechanism of the built environment through the analysis of specific urban design elements and spatial data (Spencer, 2015; Esmaeilpoorarabi et al., 2018a).

Currently, the literature focuses on several aspects of the built environment, including diversity, accessibility, and density (Zhang and Yin, 2019). Through specific indicators, such as density, mixed land use, road network connectivity, and the distance from major transportation sites, the influence of the built environment has been studied elaborately in a substantial body of literature (Carlino et al., 2007; Hamidi et al., 2019; Rammer et al., 2019; Wu et al., 2019). Studies currently focus on built environment factors and issues, like health, obesity, traffic safety, and traffic congestion. There is not much research on the impact of the built environment on RIP.

2.3 Innovation-based built environment

Based on the three paradigms of innovation and location research mentioned in the previous subsections, namely, agglomeration, diversity, and place quality, we summarize the literature on how the built environment may affects innovation productivity.

First, the agglomeration effect may be one of the means by which the built environment affects RIP. Knowledge- and innovation-based, high-tech companies tend to agglomerate in the distribution (Scott, 2000; Wu et al., 2019). These innovation subjects can benefit from sharing high-quality human resources, integrative learning opportunities, or knowledge spillovers and thus, further their own innovation (Giuliano et al., 2019). In addition to innovation clusters, universities and governments of the triple-helix model outside these clusters are likely to contribute to the establishment of local innovation capacity. Therefore, as an important aspect of the built environment, the condition of the local innovation infrastructure is crucial to RIP. Its effects include not only the urban buzz brought about by the clusters but also the connection established between local clusters and a broader global flow of knowledge through the global pipeline (Bathelt et al., 2004).

Second, the built environment may influence RIP through diversity. Beginning with Jacobs (1969), diversity has been seen as a characteristic of the city itself, and the knowledge spillover and urban buzz engendered by diversity play an important role in stimulating vitality and innovation in the city. In addition, with the introduction of such concepts as tolerance and creative class by Florida (2002), the contribution of tolerance, openness, and cultural or social diversity to regional economic development has been widely recognized in academia (Qian, 2013). Tolerance and diversity are closely intertwined with human capital and social productivity. Thus, from this point of view, a compact (Hamidi et al., 2019) and diversified built-environment development orientation may be conducive to the production of local knowledge and economic social capital and, in turn, the local innovation productivity.

Third, the built environment may affect RIP through place quality. It can promote RIP through the agglomeration of innovative talents. It is observed that investment in the development, attraction, and retention of human capital has become a key issue in the knowledge economy (Esmaeilpoorarabi et al., 2018b). In this context, it must be noted that location and lifestyle are considered important factors in the development, attraction, and retention of knowledge workers (Storper and Scott, 2009). Global cities have also embraced the knowledge-based urban development strategy to stimulate the development of RIP and promote local economies. From this perspective, the cultivation of innovation and creativity-oriented place quality can also play a crucial role in the reconstruction of the built environment in the context of the global knowledge economy. Creating a high-quality, innovative, and creativity-oriented built environment would attract and agglomerate human capital, bringing more innovative activities and driving the development of the local innovation productivity.

3 Research Design, Data, and Methodology

3.1 Research design

This study aimed to verify the impact-level of built-environment factors on the spatial heterogeneity of RIP. Our research design is shown in Fig. 1. We chose the PRD as our case study, and patent data to represent RIP. First, we built a patent-spatial database of the PRD based on geocoding technology and we verified the spa-

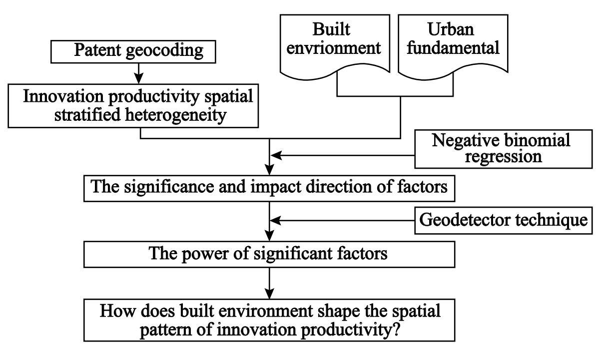

Fig. 1 Research design

tial stratified heterogeneity of PRD's innovation productivity. Second, we proposed a framework for an innovation-based built environment and construct the impact factor system. Third, we used negative binomial regression to verify the significance and the impact direction of the built-environment factors. Next, we verified the impact intensity of the significant impact factors with Geodetector. Finally, based on the model results, we discussed how the built environment shapes the spatial pattern of RIP.

3.2 Innovation-based built environment: framework and indicators

From the perspective of innovation, we tried to conceptualize the built environment more comprehensively and systematically, and developed a framework of an innovation-based built environment (Fig. 2). In this framework, we considered five aspects of an innovation-based built environment, namely, healthy environment, daily interaction, mixed land use, commuting convenience, and technology atmosphere. Based on the case of the PRD, we selected the corresponding indicators to construct the impact factor index system (Table 1).

Healthy environment. Urban environmental health conditions comprise an important consideration of knowledge workers during their selection of employment location, and these considerations are gradually influencing the regional mobility of high-quality workforces (Liu and Shen, 2014; Schoenberger and Walker, 2017). Based on the $PM_{2.5}$ data collected by 56 environmental monitoring sites in the PRD in 2017, we obtained the grid-based spatial distribution data of the average $PM_{2.5}$ concentration of the PRD in 2017 through inverse distance weighting interpolation and used it to represent the environmental health condition of the PRD.

Daily interaction. Human capital theory argues that urban amenities are increasingly important. An environment with high-quality urban amenities is conducive to attracting skilled workers; these amenities not only provide daily services but also serve as part of the social space that skilled workers require to meet and communicate (Esmaeilpoorarabi et al., 2018a; b; c; Li et al., 2019). We used grid-based living facilities' density

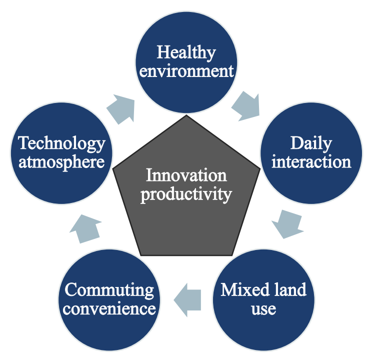

Fig. 2 Framework of the innovation-based built environment

Table 1 Summary of variables

Variables		Definition	Symbol	Expected direction	Min.	Max.	Mean	SD
Dependent Variable	Innovation productivity	Density of generated patents / (activities/km^2)	*Y*		0	1467.3300	11.1989	48.9699
Built environment	Healthy environment	$PM_{2.5}$ annual average detected value / (microgram/m^3)	HEA	–	23.7266	49.2698	35.3343	4.4526
	Technology atmosphere	Density of start-up firms / (activities/km^2)	TEC	+	0	20.6667	0.2668	0.9176
	Commuting convenience	Density of road network / (m/km^2)	COC	+	0	24.7206	2.8201	3.6332
	Mixed land use	Mix of six main land-use types	LU	+	0	1.6321	0.4849	0.4706
	Daily interaction	Density of major living facilities (Coffee shop, convenience stores, supermarkets) / (activities/km^2)	INT	+	0	113.2220	4.4359	12.4928
Urban fundamental	Local economic condition	Per capita GDP / (yuan (RMB))	GDP	+	35921	324165	92539.1534	54488.0337
	High-quality workforce	% of population with high education (undergraduate and above)	EDU	+	0.0107	0.2649	0.0450	0.0362
	Compensation	Average wage of urban residents / (yuan (RMB))	COM	+	57394	128508	69873.5107	12443.4236

(coffee shops, convenience stores, and supermarkets) to represent the level of daily interaction.

Mixed land use. Studies have shown that diverse use development significantly impacts RIP (Katz and Wagner, 2014; Hamidi and Zandiatashbar, 2018). We used the information entropy of six major land uses as indicator of diverse-use development (Wang and Wang, 2018). Entropy was proposed by Shannon (1948) to represent the degree of uncertainty of the information. It can also be used to represent the degree of mixing of information (Liu et al., 2017). The six types of land use are commercial (retail stores, restaurants, and office buildings), residential (residential areas), industrial (factories), institutional (hospitals, libraries, museums, stadiums, and primary and secondary schools), transportation (various transportation facilities), and green space and squares (parks, squares, and scenic spots).

Commuting convenience. An environment with greater commuting convenience reduces transportation costs and promotes agglomerative economies conducive to innovation (Hamidi and Zandiatashbar, 2018; Hamidi et al., 2019). In this study, we used the grid-based road network density to represent the level of commuting convenience.

Technology atmosphere. The agglomeration of various innovation subjects is the foundation of innovation. Innovation cluster brings a better technology atmosphere—not just the local urban buzz it creates but a broader global innovation pipeline (Bathelt et al., 2004). Start-ups have long been recognized as the subject of various aggressive innovations. In this study, we used grid-based start-up firms' density to represent the region's technology atmosphere.

Furthermore, we selected three indicators representing the urban fundamental as control variables, namely, compensation, local economic condition, and highly skilled workforce. We controlled the impact factor index system from three aspects—cost, economic development conditions, and human capital potential.

Compensation. As an important indicator of labor cost, the negative correlation between wage level and the concentration of manufacturing businesses has been empirically validated in several studies (Ye et al., 2019). It is also an important factor influencing the location of businesses. However, it is worth mentioning that the difference between those focusing on innovation and those on manufacturing businesses is substantial. Concerning compensation, the impact of the compensation factor on innovation productivity is yet to be explored. This study used the average wage of urban residents to represent the region's level of compensation.

Local economic condition. Florida et al. (2017) put forward the concept of 'the city as innovation machine'. The higher a city's level of economic development, the higher would be its likelihood of attracting various innovation subjects and talents and of facilitating the implementation of more innovative policies. These factors serve as the foundation of innovation productivity development. We used GDP per capital to represent the local economic condition.

High-quality labor. Human capital has a significant impact on regional and innovative growth, and the agglomeration of high-quality labor is a source of innovation and economic growth (Boschma and Fritsch, 2009; Kiuru and Inkinen, 2017). This study focuses on the impact of well-educated workforce agglomeration on innovation capacity, by using the proportion of the population with higher education (above undergraduate) to represent high-quality labor.

3.3 Study area and data source

The PRD, located on the southeastern coast of China, is known as one of China's three most developed urban agglomerations along with the Beijing-Tianjin-Hebei region and Yangtze River Delta. The PRD is composed of Guangzhou, Shenzhen, Foshan, Dongguan, Zhuhai, Zhongshan, Huizhou, Zhaoqing, and Jiangmen (Fig. 3). The PRD has a total land area of 41 711 km^2 and its resident population reached 59.1268 million in 2017.

Since the late 1980s, there has been an influx of foreign capital into the PRD, which has rapidly promoted the industrialization and urbanization of the area. As the 'world factory', the rise of the PRD is conceptualized as an effective strategic coupling between cheap production factors and global production network (Yang, 2012; Yang, 2013; Ye et al., 2019). However, since 2005, the PRD's development model has exhibited limitations due to the rise of production factors. In 2019, the central government announced the Development Plan for the Guangdong-Hong Kong-Macao Greater Bay Area. It demonstrates the PRD's ambition to transform its economic development model and achieves 'innovation-driven' development. Patent applications from the PRD accounted for 83% of those from Guangdong Province

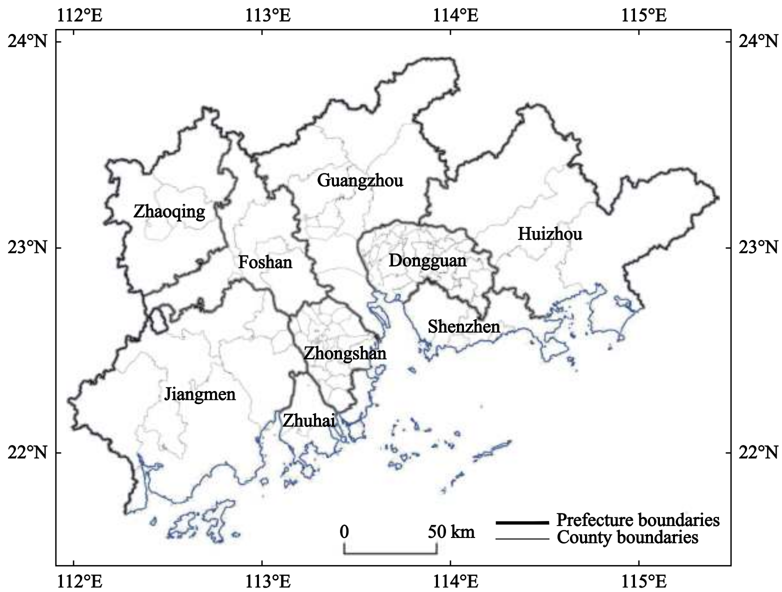

Fig. 3 Location of the Pearl River Delta

and nearly 15% of the country's total in 2017, which was more than any other province in China, except Guangdong as a whole (National Bureau of Statistics of China, 2018).

The 2017 patent data are obtained from the Patent Announcement Inquiry System of the State Intellectual Property Office of China, and include the patent name, application acceptance number, filing date, public announcement number, patent applicant, patent classification code, and detailed address information of the applicant (or organization) (https://www.cnipa.gov.cn/). Using geocoding technology, we obtained the latitude and longitude of each patent's address through the Baidu map API (https://map.baidu.com/). We established a spatial database of the PRD patterns through coordinate correction and data cleansing, which contains a total of 522 546 patent applications filed in the PRD in 2017 (Fig. 4).

The index system, with eight indicators and their data sources, is as follows. The healthy environment data were extracted from the $PM_{2.5}$ monitoring data published by the Ministry of Environmental Protection of China (http://www.mee.gov.cn/). The technology atmosphere data were extracted from a list of start-up firms published by the Guangdong Science and Technology Department in 2017 (http://sjfb.gdstc.gd.gov.cn/app/sjkf/index.jsp); we also used geocoding technology to obtain each firm's latitude and longitude coordinates and established a spatial database of 12 516 start-up firms in the PRD in 2017. The mixed land use and daily interaction data were extracted from the PRD point of interest (POI) database (https://map.baidu.com/), and the commuting convenience data were extracted from the Guangdong Province road network vector database. The urban fundamental indicator data are statistical data; of these data, the high-quality workforce data were collected from 1% Population Sample Survey Data of Guangdong in 2015, and the local economic condition and compensation data were extracted from the statistical yearbooks of each city.

3.4 Analytical model setting

As shown in Table 1, the data used in the empirical work have a nesting structure. Both RIP and built envir-

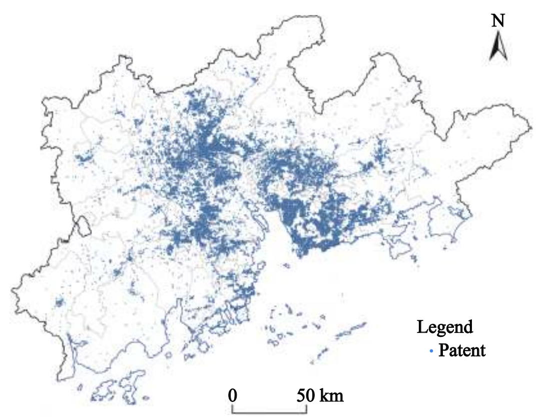

Fig. 4 The spatial distribution of patents in the Pearl River Delta

onment factors are fine-point data, while the urban fundamental data are administrative scale statistics. Introducing the concept of spatial stratified heterogeneity, we used regression analysis to examine the impact direction of the built environment factors. Second, we obtained the impact intensity of built environment factors on the spatial heterogeneity of innovation productivity using the Geodetector technique.

We divided the PRD into 5212 research units (3 km × 3 km) (Ye et al., 2019). Grid analysis avoids the effects of the distribution of natural elements, such as mountains and water bodies in administrative districts, preventing inaccuracies that emerge from the incorporation of these elements into the regression analysis. For urban fundamental data, we assigned the administrative districts data the specific grid. It is worth mentioning that since we calculated the impact intensity of the impact factors using the Geodetector technique, the scale inconsistencies of these variables will not introduce errors into the results.

First, negative binomial regression analysis is used to determine the influence direction of the built environment factors on innovation productivity (grid-based data, 5212 research units). Second, the Geodetector technique is used to determine the impact intensity of the built environment factors on the spatial heterogeneity of RIP. The Geodetector technique is a method proposed by Wang et al. (2010) to explore the stratified heterogeneity of variables. There is no requirement for the variables to be independent, which is also one of its major advantages (Wang et al., 2010; 2016; Luo et al., 2016). The impact intensity of factors can be calculated as follows:

$$p = 1 - \frac{1}{N\sigma^2}\sum_{i=1}^{n} N_i\sigma_i^2 \tag{1}$$

In the equation, N denotes the total number of samples in this study, N_i is the total number of samples in the subcategory after the classification of independent variables, i is the certain subcategory, and n is the number of independent variable categories. We used the natural breaks classification method in this study, which divided the independent variables into five categories (Wang et al., 2010, 2016). σ^2 and σ_i^2 represent the total variance of the patent spatial distribution data and the variance of patent samples in the subcategory after the independent variable classification, respectively, and p is the impact intensity of factors. As shown in Fig. 5, we applied grids to the study area and converted the spatial distribution of patents into grid property values. We can treat x and y as two different layers. The entire study area is divided into five sub-regions on the x layer. We overlaid layer y on layer x to obtain the partition of dependent variable y on the x layer. Subsequently, we calculated the impact intensity p of x on the distribution of y. $p \in [0, 1]$. The higher the p value, the higher the impact-level of independent variables on the spatial distribution of dependent variables. In this manner, we utilized another major advantage of the Geodetector technique, that is, there is no requirement for scale consistency in the independent and dependent variables. This is often regarded as a key point in the regression analysis system, as inconsistent scales of variables often lead to error in the regression model.

4 Results and Analysis

4.1 Spatial stratified heterogeneity of innovation productivity

We explored the spatial distribution characteristics of

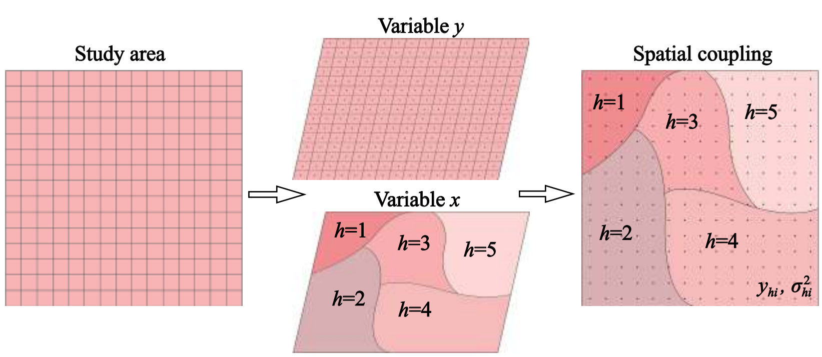

Fig. 5 Principle of Geodetector technique. h_i denotes different partitions of variable x (i = 1, 2..., 5), σ_{hi}^2 denotes the variance of y in the h_i partition (Wang et al., 2010)

the PRD's innovation productivity through a grid-based density analysis and a positive standard deviation value tail value test (Yu et al., 2015). According to the normal distribution law, mean ± σ covers about 68% of the data, and mean ± 2σ covers about 95%. We used a positive standard deviation value tail value test to draw the standard deviation line (sd line). Based on the sd line, we can visualize the high-value areas of nuclear density (Yu et al., 2015; Wu et al., 2016). The results are shown in Fig. 6. It shows that the spatial distribution of the PRD's innovation productivity is uneven, with the distribution of patents concentrated in a few areas. Areas with a higher innovation productivity are the core urban areas of Guangzhou, Shenzhen, Dongguan and Zhongshan. Positive standard deviation tail value test results (Table 2, Fig. 6) show that 416 211 patents are concentrated within the spatial range covered by the 1 sd line, accounting for 79.65% of the total number of patents. The area of the 1 sd line is merely 16.24% of the PRD. However, with a density of 61.43 patents/km^2, it is 4.9 times more concentrated than the entire study area. In other words, only 20.35% of the patents are distributed across 83.76% of the PRD's land area. The 5 sd line shows that innovation productivity peaks in Guangzhou and Shenzhen, which are also the two most developed cities in the nine PRD municipalities. According to the '2thinknow' index, the innovation capacity of Shenzhen and Guangzhou are ranked 55 th and 113 th in the world, respectively (https://2thinknow.com/), while other cities are ranked outside the top 300. This proves that the spatial distribution of the PRD's innovation productivity is extremely uneven, with a few cities monopolizing the spatial pattern.

4.2 Factors influencing the spatial heterogeneity of regional innovation productivity

We estimated the negative binomial model with Stata 12.0. Table 3 gives the results of the regression analysis. The results show that most variables are significant and with expected signs. We found that, of the five built environment factors in this study's built environment conceptual framework, four factors are significant, namely, Healthy environment (HEA), Technology atmosphere (TEC), Commuting convenience (COC), and Mixed land use (LU). Of the urban fundamental factors, Local economic condition (GDP), High-quality workforce

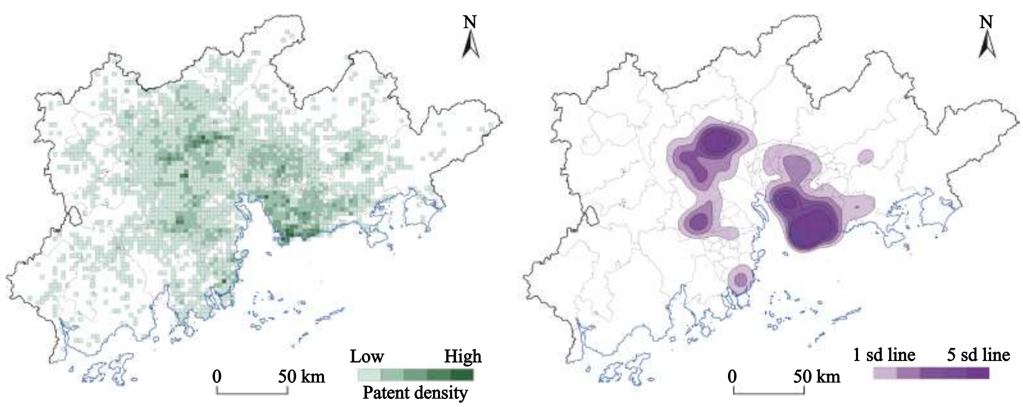

Fig. 6 The spatial heterogeneity of regional innovation productivity in the Pearl River Delta

Table 2 Results of positive standard deviation values tail values examination

Sd line	Area / km^2	Patent activities	Area proportion / %	Patent proportion / %	Count density / (patents/km^2)
PRD	41711.00	522546	100.00	100.00	12.53
1 sd line	6775.77	416211	16.24	79.65	61.43
2 sd line	3743.8	326300	8.98	62.44	87.16
3 sd line	2146.23	257780	5.15	49.33	120.11
4 sd line	1312.57	194229	3.15	37.17	147.98
5 sd line	863.51	152728	2.07	29.23	176.87

Table 3 Estimation results of negative binomial regression

Variables	Coeff.	Robust SE	z	*P*	VIF
Healthy environment	0.0155*	0.0094	1.6500	0.0990	1.3385
Technology atmosphere	0.4940***	0.0871	5.6700	0.0000	1.7917
Commuting convenience	0.4490***	0.0234	19.2100	0.0000	5.2098
Mixed land use	2.0157***	0.1072	18.8000	0.0000	1.4491
Daily interaction	–0.0080	0.0064	–1.2500	0.2130	4.2882
Local economic condition	0.0000***	0.0000	6.3400	0.0000	2.0208
High-quality workforce	4.5199***	1.6343	2.7700	0.0060	2.8935
Compensation	0.0000***	0.0000	–2.6700	0.0080	2.8192
Constant	–2.7069***	0.4654	–5.8200	0.0000	
/lnalpha	0.8444	0.0362			
Alpha	2.3266	0.0842			
Wald chi2(8) = 3068.69; Log pseudolikelihood = –9116.5051; Prob > chi2 = 0.0000					

Notes: * is significant at the 0.05 level; *** is significant at the 0.001

(EDU), and Compensation (COM) are all significant. Based on this result, we used the Geodetector technique to further explore the impact intensity of the built environment factors on the spatial differentiation of RIP.

Categorical variables must be employed in the Geodetector technique. We used the Jenks natural breaks classification method to divide the seven significant impact factors into five levels (Wang et al., 2010; 2016), from high level to low level, based on their scores; their spatial distribution is shown in Fig. 7. Based on the principle of the Geodetector technique, we calculated the impact level of the seven significant factors, as shown in Fig. 8. The factors are sorted by impact level as follows: TEC > COC > EDU > COM > LU > GDP > HEA. The Geodetector technique's results show that TEC has the greatest impact on the spatial differentiation of RIP, followed by COC, and LU and HEA have less impact on RIP. Among the urban fundamental factors, EDU has the highest level of impact.

First, technology atmosphere was found to have a significant impact on the PRD's regional innovation productivity. The negative binomial regression's results show that it is significantly positive with an impact intensity of 0.4419 in the Geodetector technique —the highest among all built environment factors. This result confirms that Marshallian specialization externalities are

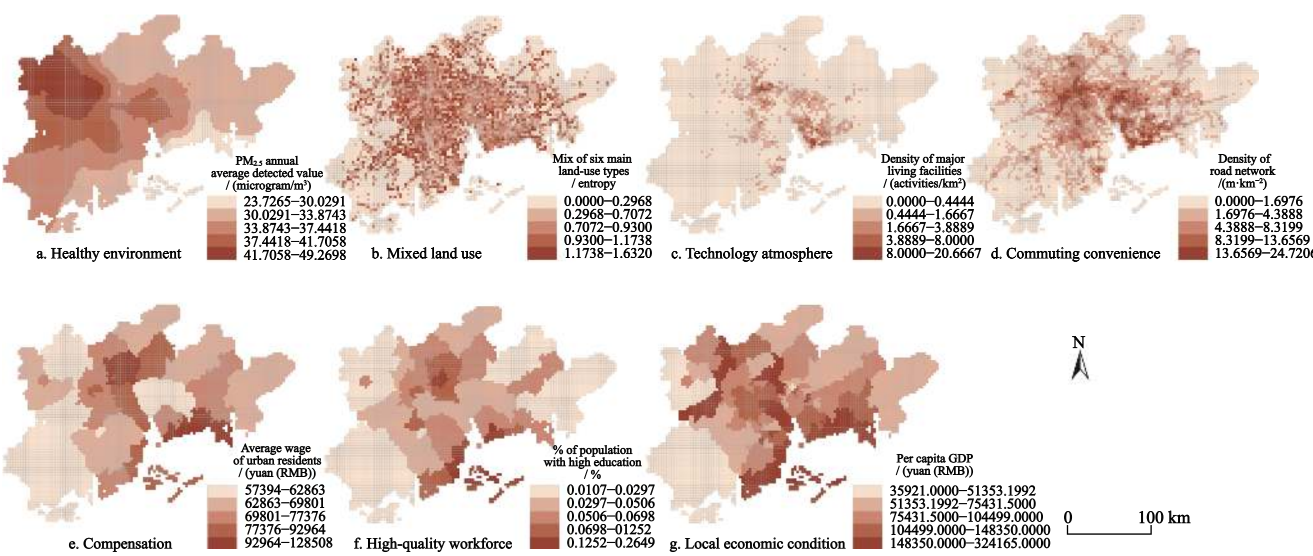

Fig. 7 Map of seven factors in relation to regional innovation productivity in the Pearl River Delta

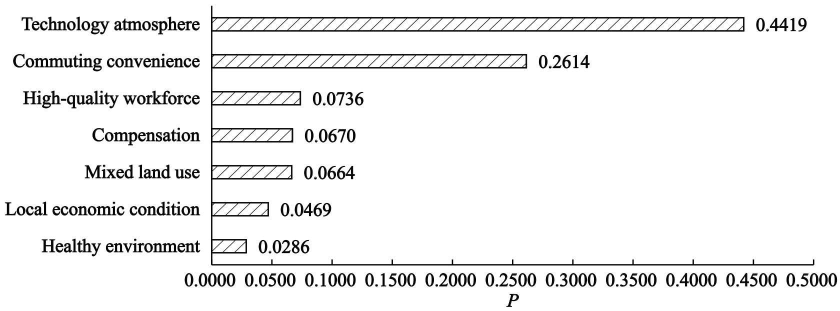

Fig. 8 Power of impact factors guiding the spatial heterogeneity of innovation productivity

conducive to the cultivation of RIP (Marshall, 1890). Fig. 7c shows that the high-value areas of technology atmosphere are mainly around the east and west banks of the Pearl River, especially around the east bank. Two distinct peaks are formed in Guangzhou and Shenzhen, which is highly correlated with the spatial pattern of the PRD's innovation productivity. The importance to innovation of a technology atmosphere and innovation actors is demonstrated in the literature on innovation systems (Albahari et al., 2018; Souzanchi Kashani and Roshani, 2019). Innovation actors and technology atmosphere have been conceptualized as important components of the regional innovation system (RIS) in the theoretical frameworks of RIS (Cooke et al., 1997), technological innovation systems (Bergek et al., 2015), sectoral innovation systems (Malerba, 2004), and triple helix (Souzanchi Kashani and Roshani, 2019). Our study also found that the spatial distribution of innovative actors has an important impact on RIP, and technology atmosphere is the most important built environment factor.

Second, commuting convenience was found to be positively correlated with RIP, and its *P*-value was 0.2614, second only to technology atmosphere. Several studies have confirmed the impact of commuting and transportation conditions on business location and industrial distribution. Regardless of whether for the industrial sector (Ye et al., 2019) or high-tech sector (Wu et al., 2019), accessibility has always been an important factor when choosing a location. Our research also confirmed that places with better commuting and accessibility conditions may have higher innovation productivity.

Third, mixed land use had a significant effect on RIP, with results showing a *P*-value of 0.0664. Mixed-use development and high-quality place making are considered conducive to facilitating social and cultural exchanges and, in turn, increasing the opportunities and effects of knowledge spillovers and generating stronger social capital (Hamidi et al., 2018). Therefore, regions with more concentrated development can provide better social and human capital, which affects innovation productivity (Zheng, 2010). This is supported by our empirical evidence.

Fourth, healthy environment was found to be positively correlated with RIP, with a *P*-value of 0.0286, which differs from our original hypothesis. In our framework, we assumed that environmental health conditions are an important consideration when knowledge workers choose their employment location, and they affect the flow of regional innovative talents and, consequently, the spatial pattern of RIP (Schoenberger and Walker, 2017). This assumption is not validated by our empirical study. This can be attributed to the development stage of the PRD and even China as a whole. At the regional level, currently, environmental health conditions have not been an important determinant of innovation productivity (Wu et al., 2019). For example, Beijing has some of the highest air pollution levels in China, but this factor has not stopped innovative talent across the country from moving into the capital city. Beijing even put forward a clear plan to control the size of its population strictly in the recent Beijing Master Plan (2016–2035) in 2017. In our empirical study, we found that healthy environment is positively correlated with innovation productivity. However, the results of the Geodetector technique show that it has a negligible impact on innovation productivity.

Fifth, daily interaction was found to have no significant impact on the spatial differentiation of innovation capacity. In our hypothesis, urban amenities, comprising basic infrastructure and a place of exchanges, form an important part of place quality and influence the workplace selection decisions of skilled workers (Esmaeilpoorarabi et al., 2018c; Lee and Kim, 2019). Hence, we assumed that daily interaction would promote RIP. However, our empirical study shows that the impact of daily interaction on innovation productivity is not significant in the PRD. We believe that one possible cause is again related to the PRD's development stage. Considered as the 'world factory', the PRD is still transitioning from a manufacturing-oriented stage to innovation-driven development, and hence, urban amenities and factors alike are yet to have a decisive effect on the flow of high-quality talent and RIP.

Sixth, the urban fundamental factors in negative binomial regression are all significant and have a positive impact on RIP. High-quality workforce has the highest level of impact among all urban fundamental factors, with a P-value of 0.0736. It is also conceptualized as part of the regional innovation system and, together with the local cultural system and industrial foundation, is considered a basic condition for innovation generation (Cooke et al., 1997). The impact level of compensation is close to that of high-quality workforce. Compensation is a representation of labor costs and an important reflection of local labor affordability. Labor costs and the concentration of manufacturing businesses have always been negatively correlated in research (Ye et al., 2019). The impact level of local economic condition on innovation capacity is 0.0469. Cities are conceptualized as innovation machines (Florida et al., 2017) in the latest literature on innovation geography. Our empirical study also shows that the higher the economic level of a city, the more vibrant and attractive it is for talent and industries (Capello and Lenzi, 2015; Aragón Amonarriz et al., 2019; Peiró-Palomino, 2019), which are both conducive to RIP.

5 Discussion and Conclusions

The spatial differentiation of innovation productivity has long been a subject of economic geography. When explaining the spatial differentiation of innovation productivity and the emergence of new knowledge, existing theories often pay more attention to the soft factors. For instance, the theoretical framework of RIS focuses on the analysis of local systems, cultures, and interactions among actors. Paradigms generated from a network perspective, such as GPN, local buzz, and global pipeline, attribute the emergence of new knowledge and innovation to local knowledge as well as the local and global knowledge connections and the spatial organization of production, with the former focusing on productive links and the latter emphasizing intellectual links. In these analytical frameworks, built environment factors are often conceptualized as part of the location factors (Marshall, 1890). There is not much systematic research discussing the impact of the built environment from an innovation perspective. A more systematic conceptualization of the innovation-based built environment would lead to a better understanding of the mechanism of the impact of the built environment on innovation.

Based on the 2017 patent spatial database of the PRD, this study constructed a framework of innovation-based built environment. Using the negative binomial regression and the Geodetector technique, it demonstrated how the built environment affects the spatial differentiation of innovation from the perspective of spatial stratified heterogeneity. Our empirical study validated the existence of such an effect, along with some unique findings.

First, the PRD's innovation productivity appears to be highly aggregated, with 79.65% of the patents concentrating in 16.24% of the land area. There is also significant spatial differentiation of innovation productivity, mainly along the east and west banks of the Pearl River, forming two large core cities in Guangzhou and Shenzhen at the regional level.

Second, our study found that the built environment has a significant effect on the spatial differentiation of innovation productivity, and there is heterogeneity in the impact intensity of different factors. Among the factors, technology atmosphere has the highest level of impact. Such empirical results confirmed the existence of Marshallian cluster externalities and proved that developing the local innovation industry and local innovation atmosphere is the key to promoting innovation productivity. Commuting convenience and mixed land use also have a significant positive effect, indicating that the mixed-use development model and the improvement of infrastructure conditions remain important means of attracting innovation subjects and talent. Additionally, they facilitate the development of the local innovation productivity. Therefore, local governments should focus on upgrading infrastructure and mixed-use development models when designing policies to promote local innovation productivity.

Third, in our framework, although we assumed that healthy environment and daily interaction exert negative and positive influences, thereby impacting innovation productivity, our empirical results show that healthy environment is positively correlated with innovation productivity but has a minor impact, while the effect of daily interaction is insignificant. This shows that environmental health conditions and place quality have not yet become decisive factors affecting the flow of highly skilled workers in the PRD's current stage of development. Our empirical results show that this transformation has not been completed, and there is still a spatial mismatch between innovation productivity and place quality. Local governments should also recognize this problem and develop more comprehensive plans to balance the innovation-oriented needs of the built environment.

Our study is one of the few to systematically examine the relationship between the built environment and spatial differentiation of innovation productivity. This study clarifies the importance of the built environment for innovation. The PRD case proves the effectiveness of the built environment framework for understanding the spatial differentiation of RIP. The model results also showed which factors are more important for cultivating innovation productivity.

The empirical study is potentially of great importance to policymakers. Recognizing the significant impact of the built environment and factor heterogeneity, the PRD local governments, when formulating local innovation development policies, should focus not only on introducing technology, building global and local connections, and constructing innovation networks, but also on ensuring an innovation-oriented built environment configuration. This focus would help them to spearhead the expansion of innovation infrastructure and urban amenities, improve the local natural and living environment, and promote mixed-use development. A combination of policies that focus on both soft and hard environments would be able to drive the development of local innovation productivity and help the PRD to gain a head start in future transitional development.

Our study has the following shortcomings. First, we used patents as the indicator of RIP. However, there are considerable innovations that do not take the form of patents. They may be reflected in the form of scientific papers and innovative products, among others. Therefore, our empirical conclusions can reflect the impact of built environment factors only on patent-oriented innovation productivity. Second, as mentioned earlier, the Geodetector technique has a unique advantage in interpreting factors in relation to the spatial differentiation of innovation productivity. It focuses on the global level examination but overlooks the heterogeneity of factors at the local level. The main directions for future research are the use of more comprehensive datasets and testing methods that can better integrate global and local factors. Third, the influencing factors of RIP have cross-regional connections. For example, Shenzhen's innovation elements and their factors may spill over to Dongguan or Huizhou. This is also a key direction for further research. It is worth mentioning that institutional factors cannot be ignored. Whether in the theoretical framework of RIS, triple helix, or GPN, institutional factors are crucial in promoting the growth of regional innovation capabilities. This study interprets the heterogeneity of innovation capabilities from the perspective of the built environment, and the discussion of institutional factors is still insufficient. This is also a potential direction for future research.

References

Adler P, Florida R, King K et al., 2019. The city and high-tech startups: the spatial organization of Schumpeterian entrepreneurship. *Cities*, 87: 121–130. doi: 10.1016/j.cities.2018.12.013

Albahari A, Barge-Gil A, Pérez-Canto S et al., 2018. The influence of Science and Technology Park characteristics on firms' innovation results. *Papers in Regional Science*, 97(2): 253–279. doi: 10.1111/pirs.12253

Aragón Amonarriz C, Iturrioz C, Narvaiza L et al., 2019. The role of social capital in regional innovation systems: creative social capital and its institutionalization process. *Papers in Regional Science*, 98(1): 35–51. doi: 10.1111/pirs.12329

Bathelt H, Malmberg A, Maskell P, 2004. Clusters and knowledge: local buzz, global pipelines and the process of knowledge creation. *Progress in Human Geography*, 28(1): 31–56. doi: 10.1191/0309132504ph469oa

Bereitschaft B, Cammack R, 2015. Neighborhood diversity and the creative class in Chicago. *Applied Geography*, 63: 166–183. doi: 10.1016/j.apgeog.2015.06.020

Bergek A, Hekkert M, Jacobsson S et al., 2015. Technological innovation systems in contexts: conceptualizing contextual structures and interaction dynamics. *Environmental Innovation and Societal Transitions*, 16: 51–64. doi: 10.1016/j.eist.2015.07.003

Boschma R, 2005. Proximity and innovation: a critical assessment. *Regional Studies*, 39(1): 61–74. doi: 10.1080/003434

0052000320887

Boschma R, Fritsch M, 2009. Creative class and regional growth: empirical evidence from seven European countries. *Economic Geography*, 85(4): 391–423. doi: 10.1111/j.1944-8287.2009.01048.x

Capello R, Lenzi C, 2015. The knowledge-innovation nexus. Its spatially differentiated returns to innovation. *Growth and Change*, 46(3): 379–399. doi: 10.1111/grow.12098

Capello R, Lenzi C, 2016. Innovation modes and entrepreneurial behavioral characteristics in regional growth. *Small Business Economics*, 47(4): 875–893. doi: 10.1007/s11187-016-9741-x

Capello R, 2017. Towards a new conceptualization of innovation in space: territorial patterns of innovation. *International Journal of Urban and Regional Research*, 41(6): 976–996. doi: 10.1111/1468-2427.12556

Capello R, Lenzi C, 2018. Regional innovation patterns from an evolutionary perspective. *Regional Studies*, 52(2): 159–171. doi: 10.1080/00343404.2017.1296943

Carlino G A, Chatterjee S, Hunt R M, 2007. Urban density and the rate of invention. *Journal of Urban Economics*, 61(3): 389–419. doi: 10.1016/j.jue.2006.08.003

Casares Blanco J, Fernández-Aracil P, Ortuño-Padilla A, 2019. Built environment and tourism as road safety determinants in Benidorm (Spain). *European Planning Studies*, 27(7): 1314–1328. doi: 10.1080/09654313.2019.1579784

Chen X F, Liu Z Y, Ma C L, 2017. Chinese innovation-driving factors: regional structure, innovation effect, and economic development-empirical research based on panel data. *The Annals of Regional Science*, 59(1): 43–68. doi: 10.1007/s00168-017-0818-5

Cooke P, Uranga M G, Etxebarria G, 1997. Regional innovation systems: institutional and organisational dimensions. *Research Policy*, 26(4–5): 475–491. doi: 10.1016/s0048-7333(97)00025-5

Crossan M M, Apaydin M, 2010. A multi-dimensional framework of organizational innovation: a systematic review of the literature. *Journal of Management Studies*, 47(6): 1154–1191. doi: 10.1111/j.1467-6486.2009.00880.x

Duan D Z, Du D B, Liu C L et al., 2016. Spatio-temporal evolution of urban innovation structure based on zip code geodatabase: an empirical study from Shanghai and Beijing. *Journal of Geographical Sciences*, 26(12): 1707–1724. doi: 10.1007/s11442-016-1354-4

Esmaeilpoorarabi N, Yigitcanlar T, Guaralda M, 2018a. Place quality in innovation clusters: an empirical analysis of global best practices from Singapore, Helsinki, New York, and Sydney. *Cities*, 74: 156–168. doi: 10.1016/j.cities.2017.11.017

Esmaeilpoorarabi N, Yigitcanlar T, Guaralda M et al., 2018b. Does place quality matter for innovation districts? Determining the essential place characteristics from Brisbane's knowledge precincts. *Land Use Policy*, 79: 734–747. doi: 10.1016/j.landusepol.2018.09.016

Esmaeilpoorarabi N, Yigitcanlar T, Guaralda M et al., 2018c. Evaluating place quality in innovation districts: a Delphic hierarchy process approach. *Land Use Policy*, 76: 471–486. doi: 10.1016/j.landusepol.2018.02.027

Ewing R, Hamidi S, Grace J B et al., 2016. Does urban sprawl hold down upward mobility? *Landscape and Urban Planning*, 148: 80–88. doi: 10.1016/j.landurbplan.2015.11.012

Fagerberg J, Srholec M, 2008. National innovation systems, capabilities and economic development. *Research Policy*, 37(9): 1417–1435. doi: 10.1016/j.respol.2008.06.003

Florida R, 2002. *The Rise of the Creative Class*. New York: Basic Books.

Florida R, Mellander C, Stolarick K, 2008. Inside the black box of regional development: human capital, the creative class and tolerance. *Journal of Economic Geography*, 8(5): 615–649. doi: 10.1093/jeg/lbn023

Florida R, Adler P, Mellander C, 2017. The city as innovation machine. *Regional Studies*, 51(1): 86–96. doi: 10.1080/00343404.2016.1255324

Freeman C, 2002. Continental, national and sub-national innovation systems: complementarity and economic growth. *Research Policy*, 31(2): 191–211. doi: 10.1016/s0048-7333(01)00136-6

Furman J L, Porter M E, Stern S, 2002. The determinants of national innovative capacity. *Research Policy*, 31(6): 899–933. doi: 10.1016/s0048-7333(01)00152-4

Giuliano G, Kang S, Yuan Q, 2019. Agglomeration economies and evolving urban form. *The Annals of Regional Science*, 63(3): 377–398. doi: 10.1007/s00168-019-00957-4

Hamidi S, Ewing R, 2015. Is sprawl affordable for Americans? Exploring the association between housing and transportation affordability and urban sprawl. *Transportation Research Record*, 2500(1): 75–79. doi: 10.3141/2500-09

Hamidi S, Zandiatashbar A, 2018. Does urban form matter for innovation productivity? A national multi-level study of the association between neighbourhood innovation capacity and urban sprawl. *Urban Studies*, 56(8): 1576–1594. doi: 10.1177/0042098018767002

Hamidi S, Zandiatashbar A, Bonakdar A, 2019. The relationship between regional compactness and regional innovation capacity (RIC): empirical evidence from a national study. *Technological Forecasting and Social Change*, 142: 394–402. doi: 10.1016/j.techfore.2018.07.026

Jacobs J, 1969. *The Economy of Cities*. New York: Vintage.

Katz B, Wagner J, 2014. *The Rise of Innovation Districts: A New Geography of Innovation in America*. Washington, DC: Metropolitan Policy Program at Brookings.

Kiuru J, Inkinen T, 2017. Predicting innovative growth and demand with proximate human capital: a case study of the Helsinki metropolitan area. *Cities*, 64: 9–17. doi: 10.1016/j.cities.2017.01.005

Lee H K, Kim H B, 2019. Regional preferences for the living environment and mobility of researchers and general workers: the case of Korea. *Annals of Regional Science*, 62(1): 169–186. doi: 10.1007/s00168-018-0892-3

Li H, Wei Y D, Wu Y Y, 2019. Urban amenity, human capital and employment distribution in Shanghai. *Habitat International*, 91: 102025. doi: 10.1016/j.habitatint.2019.102025

Li Y C, Phelps N A, 2018. Articulating China's science and technology: knowledge collaboration networks within and beyond the Yangtze River Delta megalopolis in China. *Chinese Geographical Science*, 28(2): 247–260. doi: 10.1007/s11769-018-0944-8

Liu Q Q, Wang S J, Zhang W Z et al., 2017. China's municipal public infrastructure: estimating construction levels and investment efficiency using the entropy method and a DEA model. *Habitat International*, 64: 59–70. doi: 10.1016/j.habitatint.2017.04.010

Liu Y, Shen J F, 2014. Jobs or amenities? Location choices of interprovincial skilled migrants in China, 2000–2005. *Population, Space and Place*, 20(7): 592–605. doi: 10.1002/psp.1803

Luo W, Jasiewicz J, Stepinski T et al., 2016. Spatial association between dissection density and environmental factors over the entire conterminous United States. *Geophysical Research Letters*, 43(2): 692–700. doi: 10.1002/2015gl066941

Lv Lachang, Sun Feixiang, Huang Ru, 2019. Innovation-based urbanization: evidence from 270 cities at the prefecture level or above in China. *Journal of Geographical Sciences*, 29(8): 1283–1299. doi: 10.1007/s11442-019-1659-1

Ma Haitao, Fang Chuanglin, Pang Bo et al., 2015. Structure of Chinese city network as driven by technological knowledge flows. *Chinese Geographical Science*, 25(4): 498–510. doi: 10.1007/s11769-014-0731-0

Malerba F, 2004. *Sectoral Systems of Innovation: Concepts, Issues and Analyses of Six Major Sectors in Europe*. Cambridge: Cambridge University Press.

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

National bureau of statistics of China, 2018. *China Statistical Year Book*. In: Beijing Chinese Statistics Bureau.

Ozgen C, Nijkamp P, Poot J, 2017. The elusive effects of workplace diversity on innovation. *Papers in Regional Science*, 96: S29–S50. doi: 10.1111/pirs.12176

Peiró-Palomino J, 2019. The geography of social capital and innovation in the European Union. *Papers in Regional Science*, 98(1): 53–73. doi: 10.1111/pirs.12337

Porter M E, 1998. *Competitive Advantage of Nations*. New York: Free Press.

Proksch D, Haberstroh M M, Pinkwart A, 2017. Increasing the national innovative capacity: identifying the pathways to success using a comparative method. *Technological Forecasting and Social Change*, 116: 256–270. doi: 10.1016/j.techfore.2016.10.009

Qian H F, 2013. Diversity versus tolerance: the social drivers of innovation and entrepreneurship in US cities. *Urban Studies*, 50(13): 2718–2735. doi: 10.1177/0042098013477703

Rammer C, Kinne J, Blind K, 2019. Knowledge proximity and firm innovation: a microgeographic analysis for Berlin. *Urban Studies*, 57(5): 996–1014. doi: 10.1177/0042098018820241

Schoenberger E, Walker R A, 2017. Beyond exchange and agglomeration: resource flows and city environments as wellsprings of urban growth. *Journal of Economic Geography*, 17(5): 935–958. doi: 10.1093/jeg/lbw012

Scott A J, 2000. Economic geography: the great half-century. *Cambridge Journal of Economics*, 24(4): 483–504. doi: 10.1093/cje/24.4.483

Shannon C E, 1948. A mathematical theory of communication. *The Bell System Technical Journal*, 27(3): 379–423. doi: 10.1002/j.1538-7305.1948.tb01338.x

Souzanchi Kashani E, Roshani S, 2019. Evolution of innovation system literature: intellectual bases and emerging trends. *Technological Forecasting and Social Change*, 146: 68–80. doi: 10.1016/j.techfore.2019.05.010

Spencer G M, 2015. Knowledge neighbourhoods: urban form and evolutionary economic geography. *Regional Studies*, 49(5): 883–898. doi: 10.1080/00343404.2015.1019846

Storper M, Scott A J, 2009. Rethinking human capital, creativity and urban growth. *Journal of Economic Geography*, 9(2): 147–167. doi: 10.1093/jeg/lbn052

Sun B D, Yin C, 2018. Relationship between multi-scale urban built environments and body mass index: a study of China. *Applied Geography*, 94: 230–240. doi: 10.1016/j.apgeog.2018.03.012

Van Winden W, de Carvalho L, van Tuijl E et al., 2012. *Creating Knowledge Locations in Cities*. London: Routledge.

Wang J F, Li X H, Christakos G et al., 2010. Geographical detectors-based health risk assessment and its application in the neural tube defects study of the Heshun Region, China. *International Journal of Geographical Information Science*, 24(1): 107–127. doi: 10.1080/13658810802443457

Wang J F, Zhang T L, Fu B J, 2016. A measure of spatial stratified heterogeneity. *Ecological Indicators*, 67: 250–256. doi: 10.1016/j.ecolind.2016.02.052

Wang Yuming, Wang Ruikang, 2018. Reasons for the increasing information entropy of suburban land use structure during the period of urbanization. *Acta Geographica Sinica*, 73(9): 1647–1657. (in Chinese)

Wixe S, 2018. Neighbourhood related diversity, human capital and firm innovation. *Papers in Regional Science*, 97(2): 217–253. doi: 10.1111/pirs.12255

Wood S, Dovey K, 2015. Creative multiplicities: urban morphologies of creative clustering. *Journal of Urban Design*, 20(1): 52–74. doi: 10.1080/13574809.2014.972346

Wu Kangmin, Zhang Hongou, Wang Yang et al., 2016. Identify of the multiple types of commercial center in Guangzhou and its spatial pattern. *Progress in Geography*, 35(8): 963–974. (in Chinese). doi: 10.18306/dlkxjz.2016.08.005

Wu K M, Wang Y, Ye Y Y et al., 2019. Relationship between the built environment and the location choice of high-tech firms: evidence from the Pearl River Delta. *Sustainability*, 11(13): 3689. doi: 10.3390/su11133689

Yang C, 2012. Restructuring the export-oriented industrialization in the Pearl River Delta, China: institutional evolution and emerging tension. *Applied Geography*, 32(1): 143–157. doi: 10.1016/j.apgeog.2010.10.013

Yang C, 2013. From strategic coupling to recoupling and decoupling: restructuring global production networks and regional evolution in China. *European Planning Studies*, 21(7): 1046–1063. doi: 10.1080/09654313.2013.733852

Yang C, 2014. State-led technological innovation of domestic firms in Shenzhen, China: evidence from liquid crystal display (LCD) industry. *Cities*, 38: 1–10. doi: 10.1016/j.cities.2013.12.005

Yang J W, Zhou P L, 2020. The obesity epidemic and the metropolitan-scale built environment: examining the health effects of polycentric development. *Urban Studies*, 57(1): 39–55. doi: 10.1177/0042098019844177

Ye Y Y, Wu K M, Xie Y C et al., 2019. How firm heterogeneity affects foreign direct investment location choice: micro-evidence from new foreign manufacturing firms in the Pearl River Delta.*AppliedGeography*,106:11–21.doi:10.1016/j.apgeog.2019.03.005

Yu W H, Ai T H, Shao S W, 2015. The analysis and delimitation of Central Business District using network kernel density estimation. *Journal of Transport Geography*, 45: 32–47. doi: 10.1016/j.jtrangeo.2015.04.008

Zandiatashbar A, Hamidi S, 2018. Impacts of transit and walking amenities on robust local knowledge economy. *Cities*, 81: 161–171. doi: 10.1016/j.cities.2018.04.005

Zhang F Z, Wu F L, 2019. Rethinking the city and innovation: a political economic view from China 's biotech. *Cities*, 85: 150–155. doi: 10.1016/j.cities.2018.09.003

Zhang H, Yin L, 2019. A meta-analysis of the literature on the association of the social and built environment with obesity: identifying factors in need of more in-depth research. *American Journal of Health Promotion*, 33(5): 792–805. doi: 10.1177/0890117118817713

Zheng W, 2010. A social capital perspective of innovation from individuals to nations: where is empirical literature directing us? *International Journal of Management Reviews*, 12(2): 151–183. doi: 10.1111/j.1468-2370.2008.00247.x