



Examining the Effects of the Built Environment on Housing Rents in the Pearl River Delta of China

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Abstract

Rent levels are a core indicator of the local housing market. Although existing studies have examined various factors influencing local rent levels, there is no systematic research on the impacts of the built environment on housing rents. This paper examines the mechanisms by which the built environment affects rents from five theoretical perspectives. Taking the Pearl River Delta (PRD) of China as a case study, four indicators—mixed land use (MLU), public service level (PSL), high-rise buildings (HRB), and air pollution (AP)—are used to represent the four aspects of the local built environment, namely, land use, public facilities & services, architectural scale, and health & comfort, respectively. The spatial regression and geodetector techniques are combined to illustrate the significant impacts of the built environment on housing rents. The results of Moran's I test reveal the existence of significant spatial autocorrelation of rents in the PRD. From the spatial regression analysis, this paper concludes that the degree of mixing of land use, the proportion of high-rise residential buildings, and the air pollution negatively impact housing rents. In contrast, the density of public service facilities positively affects housing rents. These findings are in line with the theoretical projections. The geodetector technique indicates that the effects of the four aspects of the built environment on housing rents are significantly different. AP has the strongest influence on housing rents. Our findings show that the built environment is an important factor affecting the local housing market. Improving the built environment should be carefully considered by decision-makers when they formulate cities' development strategies and draw up local housing development plans.

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Introduction

At present, approximately 1.2 billion people rely on renting to fulfill housing needs (Gilbert, 2016). In China, the demand for rental housing has been growing for the past two decades (Cui et al., 2018), and the rental market has become an indispensable component of the housing market. The proportions of people living in rentals in the Pearl River Delta (PRD), a major city cluster in China, are extremely high. For instance, in Shenzhen, 72.68% of the people live in rented apartments or houses, while the proportions are 40.58% in Guangzhou, 62.48% in Dongguan, and 46.26% in Zhongshan (based on the 1% population sampling survey conducted in urban areas nationwide in 2015). The housing rental market is a substantial part of the housing market in the PRD, and it is the only affordable way for most migrant workers from other parts of China to fulfill their housing needs.

Rent levels are a core indicator of the rental housing market, and in the PRD, housing rents vary considerably. Nanshan District, Shenzhen, has the highest housing rents, with an average rent of 98.26 RMB/month·m². In contrast, the average rent in Gaoming District, Foshan, is only 18.22 RMB/month·m². The former is 5.39 times the latter. Analyzing the factors influencing housing rents is key to gaining deeper insights into the mechanism determining housing rents and can provide a basis for the precise design of policies for rental housing. Therefore, it is necessary to analyze the factors underlying the different rent levels in the PRD.

Regional rent differences are determined by the demand and supply of housing rentals and urban fundamentals. Empirical studies have shown that population inflow, employment opportunities, income levels (ILs), and urban livability are the factors influencing regional rent levels (Glaeser et al., 2000; Mussa et al., 2017; Potepan, 1996; Saiz, 2007). To date, few papers have examined the influences of the built environment. The built environment is an important component of urban fundamentals. Theoretically, the built environment significantly impacts people's urban housing choices and further affects the structure of the housing market (such as housing prices or rent levels). Therefore, it is imperative to analyze and explain the routes and mechanisms by which the built environment influences rent levels and to empirically exam whether these influences are significant. The built environment refers to the physical surroundings and often consists of multiple dimensions, such as diversity, accessibility, density, and buildings (Wu et al., 2021a; Wu & Niu, 2019; Zhang & Yin, 2019). Which elements of the local built environment are significant? How strong is the impact? These are all questions needing answers.

To fill the research gap, first, we theoretically analyze how the built environment can affect regional rent levels, and the routes and mechanisms by which the built environment influences rent levels are identified. Second, a case study on the PRD is conducted, in which we use the spatial regression model to test whether the built environment has significant effects. Third, the geodetector technique is used to measure the influences of the built environment on the spatial heterogeneity of rent levels. The above assessments are of theoretical value and can support policymaking

to improve built environments, create livable cities, and manage housing rental markets.

The innovations and contributions of this paper are as follows, first, the theoretical path of built environment influences rent levels is proposed from five perspectives. It expounds theoretically the impact of the built environment on rents, and enriches the theoretical framework of the factors affecting regional rents from the perspective of the built environment, which has rarely been considered in previous studies. Second, taking the PRD of China as a case, it verified that the built environment has a significant impact on rents. This paper supplements the existing research results on the factors affecting rents from the perspective of the built environment, and it also enriches the case study of Global South.

The remainder of this paper is organized as follows. In Section 2, the relevant studies on the built environment and housing rent are summarized. In Section 3, the routes and mechanisms by which the built environment influences rent levels are analyzed from five theoretical perspectives. Section 4 is the research design, data, and methodology. Section 5 presents the results and discussion, including the spatial patterns of housing rents and the impact direction, significance, and intensity of the impact of built environment elements on rent levels, and offers explanations for the findings. Section 6 presents the conclusions of the paper.

Literature Review

The Concept of the Built Environment and its Influences on the Housing Market

The built environment refers to human-made surroundings and mainly consists of diversity, accessibility, density, and buildings (Wu & Niu, 2019; Zhang & Yin, 2019). The main indicators used in existing assessments of the built environment include mixed land use (MLU), public facility density, road network connectivity, distance from major transportation sites, and building characteristics (Carlino et al., 2007; Hamidi et al., 2019; Rammer et al., 2020; Wu et al., 2019; Wu & Niu, 2019). The built environment influences health (Smit & Tucker, 2019), crime rates (Groff, 2017), amenities (Reeder et al., 2019), traffic conditions (Pan et al., 2020), car ownership or the willingness to use cars (Li & Zhao, 2017), local urban climate (Mabon et al., 2019), urban vitality (Wu & Niu, 2019), and competitiveness (Kresl & Ietri, 2017).

Existing studies have investigated how the built environment affects the housing location choice and housing prices. As early as 1988, Clark (1988) noted the relationship between the built environment and rents. Scott (1997) used the hedonic price model to assess the built environment's influences on housing prices and further evaluated the externality values of the built environment. Bhat and Guo (2007) analyzed the housing choices of the residents in the San Francisco Bay area and found that the built environment has significant effects, which are generated through its influences on the car ownership and travel mode choices of residents. Liao et al. (2015), who studied the Wasatch Front region in Utah, reported that one element of the built environment, the presence of compact, walkable, transit-friendly

neighborhoods, has important effects on residents' choices of housing locations. Ettema and Nieuwenhuis (2017) analyzed the influences of the built environment on people's housing location choices from the perspective of travel modes. Kroesen (2019) showed that the built environment can influence people's attitudes toward travel and further affect their choices of housing locations.

These studies provide a theoretical and empirical basis for the present study on the built environment's effects on housing rent levels. To date, few studies have analyzed the effects of the built environment on housing rents. In the following section, the main factors influencing local rent levels and the channels of the built environment's effects on rent levels are analyzed.

The Factors Influencing Rent Levels and the Role of the Built Environment

Rent levels are an important indicator of local housing markets, and the theoretical frameworks employed to analyze the factors influencing rent levels are generally the same as those adopted to identify the factors affecting housing prices. There are more empirical studies on the factors influencing local housing prices. The theoretical approaches can be summarized as the demand/supply approach and the urban fundamentals approach.

In the demand/supply approach, population is the core indicator for assessing housing demand. Population influence housing demand through population growth (PG) (Haron & Liew, 2013; Mussa et al., 2017), population shrinkage (Maennig & Dust, 2008), and population flow (population inflow from other places) (Wang et al., 2017a, 2017b). In terms of housing supply, the higher the elasticity of the housing supply is, the smaller the increase in housing prices (Grimes & Aitken, 2010; Liebersohn, 2018).

Urban fundamentals are another important research approach. Studies adopting this approach are often based on the hedonic price model (Bitter et al., 2007; Can, 1992). The urban fundamentals approach mainly focuses on city economic development levels (Hossain & Latif, 2009; Vogiazas & Alexiou, 2017), the urban economic structure with the development level of the service industry as the main indicator (Shen & Liu, 2004), and the urban housing market environment (Hwang & Quigley, 2006). Income is both an element of urban fundamentals and a factor affecting purchasing power for housing, which in turn affects the demand for housing. Income is often represented by indicators such as per capita disposable income (Holly et al., 2010), permanent income (Goodman, 1988), and salary (Wang & Zhang, 2014).

Empirical studies on the factors influencing rent levels indicate that household income and construction costs are the most important factors influencing the rent differences among major cities in the US. Eaton and Eckstein (1997) found that the higher the level of human capital is, the higher the housing rent. Glaeser et al. (2000) showed that rent grows faster in cities with high amenity and comfort levels. Quigley and Raphael (2004), who studied housing rent affordability in the US, indicated that IL is positively correlated with the rent level. Saiz (2007) showed that every 1% increase in the population inflow to a metropolitan area in the US causes a 1% increase in housing rent. Work by Nakagawa et al. (2007) on the Tokyo metropolitan area

revealed that the housing rent is far lower in areas with high earthquake risk than in safe areas. Matlack and Vigdor (2006) analyzed the housing market data of US metropolitan areas and noted that in markets with low vacancy rates, a positive correlation exists between income growth and rent increases. A study by Diamond (2016) on the US found that the higher the concentration of university graduates is, the higher the housing rent. Mussa et al. (2017) showed that population inflow has both direct and indirect effects on the US housing market. H. Li et al. (2019) analyzed the housing rental market in Shanghai and discovered that at the local level, employment opportunities, salary levels, and the size of the "mobile" population can affect housing rents. In summary, the existing studies on the factors influencing regional rent mainly focus on population inflow, IL, and urban amenity and comfort levels.

Many studies that have adopted a microscopic view have found that certain elements of the built environment, such as parks, land use intensity, access to public facilities, transport accessibility, and polluting infrastructure facilities, influence housing prices or housing rents (Efthymiou & Antoniou, 2013; Filippini et al., 2008; Gurran & Phibbs, 2017; Kang, 2019; Liebelt et al., 2019; Yang et al., 2018). These studies mainly demonstrate such influences by establishing hedonic price models. Only a few studies assess the impacts of the built environment on housing prices. Diao and Ferreira (2010) analyzed the relationship between the built environment and housing property values in the Boston metropolitan area in the US and found that housing prices are positively correlated with the accessibility of transit and jobs, connectivity, and walkability. Huang and Yin (2015) conducted a case study on Wuhan about how built environment elements, such as green spaces, public transport systems, and proximity to the central business district (CBD), affect local housing prices. Their results showed that when natural water resources, culture, tourism, and commercial resources integrate and form natural amenity clusters or areas, their positive effects on housing are most significant. These studies suggest a certain influence of built environment elements on the housing market. However, we need to further analyze the impact of the built environment on rents, because renting is an important part of the housing market. The next section discusses the relationships between the built environment and housing rent and the ways in which the built environment can affect rent levels.

How Does the Built Environment Affect Housing Rent Levels?

The above literature review indicates that the built environment significantly affects rent levels. In this section, the channels by which the built environment influences rent levels are elaborated from five perspectives. From these perspectives, there are four aspects of built environment factors that affect the difference in rents (Fig. 1).

First, the theory of public goods can explain how the built environment affects rent levels. Tiebout (1956) developed the theory of public goods from the perspectives of political economics and public economics. He believed that the supply of local public goods and taxation policy differences determined people's choices of housing locations due to people's different abilities to pay and preferences for local public goods, creating the classic Tiebout model. The built environment elements

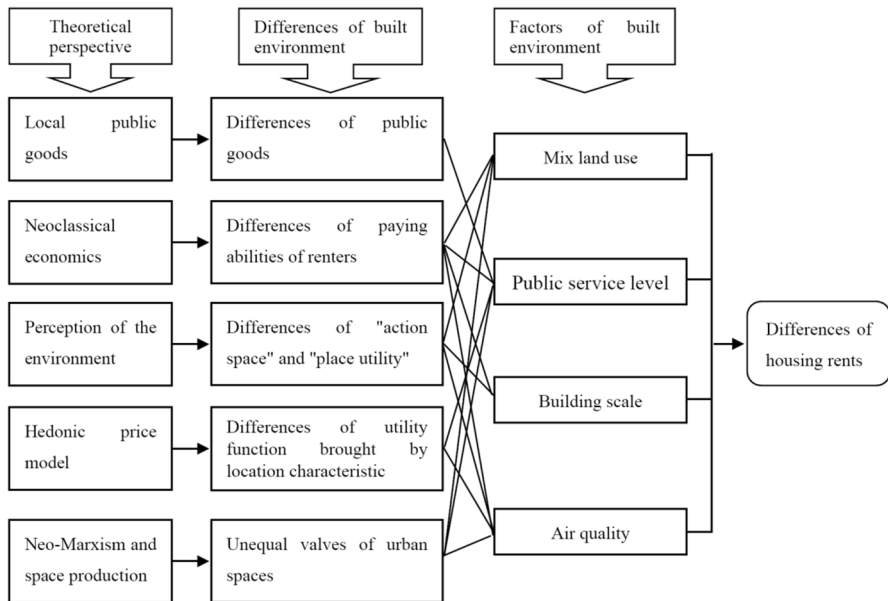


Fig. 1 The theoretical explanation of effects of the built environment on housing rents

of roads, public service facilities, and infrastructure are important components of local public goods. The built environment can be seen as an embodiment of local public goods. Areas with high-quality built environments are more attractive and competitive (Kresl & Ietri, 2017). Theoretically, areas with higher quality built environments have higher rents. From this perspective, the public service level factor affects the rent level.

Second, the market equilibrium theory of neoclassical economics, which is based on the assumption of rent balance maximization, can explain the relationship between the built environment and rent levels. On the basis of this theory, Herbert and Stevens (2006) analyzed people's living location choices from the macroeconomic balance approach and concluded that people with the highest rent-paying abilities would choose the best housing locations. The relationship between the built environment and housing location choice is very strong, and the built environment is an important factor in the evaluation of housing location quality. Therefore, this theory concludes that people wanting a high-quality built environment have to pay high rent. From this perspective, the main factors of the built environment (for example, mix land use, public service level, building scale, air quality, etc.) theoretically affect the regional rent level.

Third, environmental perceptions offer an explanation for how the built environment affects rent levels. Wolpert (2005) proposed that people's housing location choices are based on their perception of the environment. He further proposed the basic concepts and research perspectives of "action space" and "place utility" and introduced environmental perceptions into an analytical framework of housing location choices. From environmental behavior perspective, Färe and Knox Lovell

(1978) found that when selecting housing, in addition to consumers' desired household features, subjective elements such as their previous house-buying experiences, culture, values, emotions, and preferences can all influence their housing choices. The built environment shapes the action space, embodies place utility, and is a core factor determining a resident's environmental perception (Greenwald et al., 2001). Some studies indicate that the built environment has a major impact on people's psychology (Guite et al., 2007). When selecting a housing location, people tend to choose locations with a good built environment. Hence, they need to pay high rent to secure housing in such locations. From this theoretical perspective, factors such as mix land use, building scale, and air quality affect the level of housing rent.

Fourth, the effects of the built environment on rent levels can be justified from the perspective of the utility function and hedonic price theory. Rosen (1974) believed that goods are valued for their utility-bearing attributes or characteristics. From this perspective, a property's total price can be regarded as the sum of all its features, and in market equilibrium, each feature has a unique implicit price. Thus, the price of a commodity can be regressed on its features to determine the unique contributions of each feature to the composite unit price. This theory is the main methodology employed in contemporary element-based analysis of housing prices. The built environment consists of elements such as landscape, traffic conditions, public facilities, green area, and environmental perception (such as noise and air quality) and is an important feature of a housing property and a component of a home's implicit price. Empirical studies have demonstrated the above elements' influences on housing rents (Efthymiou & Antoniou, 2013; Filippini et al., 2008; Gurran & Phibbs, 2017; Leung & Yiu, 2019; Zambrano-Monserrate & Alejandra Ruano, 2019). The built environment influences the utility of rental homes. Therefore, this theory indicates that the rent is higher for housing with a better built environment. From this perspective, factors such as public service level and air quality affect housing rents.

Fifth, neo-Marxism contends that the differences in the built environment form unequal urban spaces and generate local gentrification effects and rent differences (due to improvements to the built environment) (Harvey, 1973; Smith, 1987). Urban space appears as an object for environmental assessment, which can boost various efforts at urban space diversification (sociocultural diversity and creativity) and can be interpreted as the process of value generation for urban spaces (Stehlin, 2016). Gentrification implies a high quality of built environments and higher rent. Based on this theoretical perspective, the main factors of the built environment (for example, mix land use, public service level, air quality affect housing rent).

Research Design, Data, and Methodology

Study Area

The PRD, located in a coastal area in southern China, is one of the three most advanced city clusters in China. It includes Guangzhou, Shenzhen, Foshan, Dongguan, Zhuhai, Zhongshan, Huizhou (excluding Longmen County), Zhaoqing (excluding Deqing, Huaiji, Fengkai, and Guangning Counties), and Jiangmen

(Fig. 2). In 2018, there were 58.88 million permanent residents in the PRD. Guangzhou and Shenzhen are the two core cities of the PRD. The PRD has an advanced economy and high population density, and its housing prices are high relative to others in China (Wang et al., 2017a, 2017b). Due to the area's large mobile population, the share of people living in rented homes is high, reaching 45.52% of the total (2015 data). This study takes counties, county-level cities, and districts as the basic research units (hereafter referred to as "counties"), of which there are 54 in the PRD.

Research Design

Given the built environment elements reported to affect housing rents, this analysis evaluates the built environment in terms of four aspects: mix land use (MLU), public service level (PSL), high-rise buildings (HRB), and air pollution (AP). These four aspects represent land use, public services, architectural scale, and health perception, respectively, which are all key elements of the built environment. The analysis also considers four indicators that may affect urban fundamentals and housing rent levels, namely, population growth (PG), living space (LS), illiterate population (IP), and Income level (IL). These four indicators can reflect the demand and supply of rental houses and rent affordability in a city. These eight indicators together form our evaluation system for the factors influencing housing rents.

On the basis of the above evaluation system, spatial autocorrelation is used to assess whether there is spatial autocorrelation among the housing rent levels in different parts of the PRD. Then, spatial regression is used to evaluate the significance and direction of each influencing factor. Thereafter, the geodetector technique is applied to study in detail the influences of the different factors. Finally, the results are interpreted to explain how these built environment elements affect housing rent (Fig. 3).

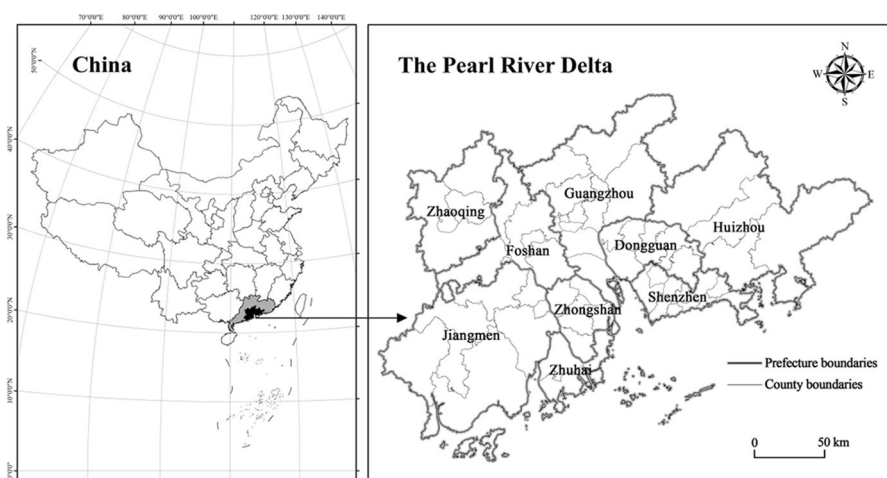


Fig. 2 The Pearl River Delta

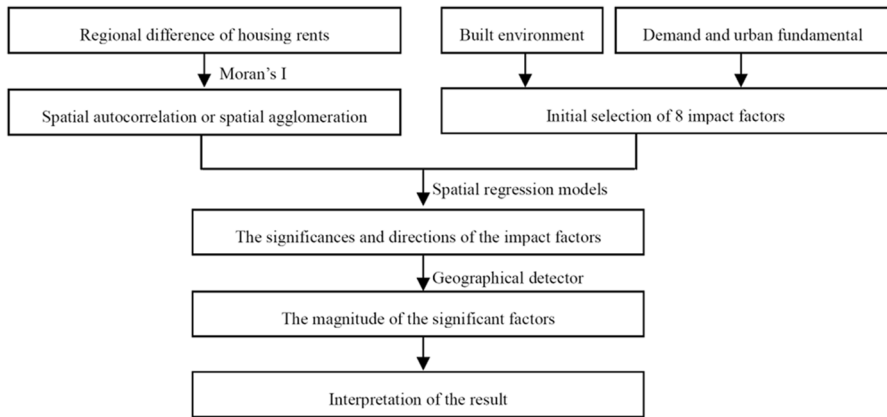


Fig. 3 Research design

The four elements of the built environment and their evaluation methods are presented as follows:

MLU. Some studies show that MLUs with positive functions can increase the diversity of functions and improve built environment quality. One example is the mixed commercial–residential function (Rundle et al., 2007) or a combination of stores, offices, parks, and other functions (Zhang et al., 2012). However, from the perspective of livability, MLU, especially land uses that negatively impact housing (e.g., factories, urban infrastructure), can cause noise, pollution, congestion, etc., and deteriorate residents' living experience. Moreover, such MLUs have negative impacts on the built environment. Specifically, the information entropy of six major land uses is calculated and used as an indicator. Six major land uses include residential (including residential area), industry (including factory), business & services (including Office building, retail, Catering), public services (including library, hospital, museum, stadium, Primary and secondary school), green space (including park, Scenic spot, square), transportation facilities (including various transportation facilities).

PSL. PSL is a core element of a city's attractiveness and competitiveness. Comprehensive and high-quality PSL can improve the built environment of a place, attract more highly skilled residents (Esmailpoorarabi et al., 2018), and raise housing prices (Wen et al., 2018). Therefore, in theory, there is a positive correlation between PSL and housing rent. The density of basic public service facilities (primary schools, middle schools, hospitals, museums, sports facilities) is used to measure the PSL.

HRB. Building characteristics are an important component of the built environment (Kylili et al., 2016), and the sizes of buildings influence the built environment (Lu et al., 2019). Some studies have shown that HRBs have negative psychological effects on people (Kearns et al., 2012). Too many HRBs in an urban space can make people feel depressed, thereby reducing the built envi-

ronment quality. In addition, the floor area ratio of HRBs is often high, leading to high population density and a worsened living environment. Therefore, in theory, the number or proportion of HRBs is negatively correlated with rent level. In China, buildings with 10 or more floors are defined as HRBs. The proportion of high-rise (10 or more floors) residential buildings (%) is used as the evaluation indicator for HRB in this paper.

AP. In terms of living experience, AP can be directly experienced by residents and determine their impressions of built environment quality (King, 2015; Zhou & Lin, 2019). Empirical studies indicate a strong correlation between AP and rent levels (Cobb, 1977; Zhou & Lin, 2019). The fine particulate matter (up to 2.5 μm in diameter, $\text{PM}_{2.5}$) concentration is the most important indicator of AP (Liang et al., 2016) and one environmental quality indicator to which residents pay close attention. Excessive $\text{PM}_{2.5}$ levels can damage people's health (Guan et al., 2019). The grid-based $\text{PM}_{2.5}$ monitor value is obtained through inverse distance weighting interpolation of data from 56 monitoring stations (2017). In theory, AP ($\text{PM}_{2.5}$ concentration) is expected to be negatively correlated with housing rent.

Housing demand and four elements of urban fundamentals are used as the control variables in this study, and the considerations and evaluation methods are presented as follows (some descriptions are brief, and more details are given later in this paper):

PG. PG can generate housing demand and reflects the attractiveness of a city. Some studies indicate a positive correlation between PG and housing rent levels (Mussa et al., 2017; Saiz, 2007). The density of permanent PG during 2016–2018 is used to measure the PG of each county. In theory, it was expected that PG would have a positive correlation with housing rent levels.

LS. Per capita floor area can indicate the amount of LS and is an important indicator of the degree of crowding, the difficulty of finding housing, and the demand for housing improvement in a city. The smaller the per capita floor area is, the more difficult it will be to find housing (C. Zhang, 2015) and the higher the rents will be. Hence, in theory, LS is expected to be negatively correlated with housing rent levels.

IP. The lower the IP proportion in a region, the higher the education level of the residents and the better the population quality and cultural atmosphere. IP is a key indicator of urban fundamentals. The proportion of IP is used as the indicator for evaluating IP. In theory, the lower the proportion of IP, the higher the rent; they are negatively correlated.

IL. In Chinese national statistics, the average wage of employed staff and workers is a common indicator of IL. IL is closely related to housing rent affordability (Colburn & Allen, 2018), represents people's tolerance of rent levels, and reflects a city's overall development levels and residents' IL. Some case studies show that in cities, the higher the IL is, the higher the rent (Eaton & Eckstein, 1997; H. Li et al., 2019; Matlack & Vigdor, 2006; Potepan, 1996). In theory, there would be a positive correlation between these factors.

According to the above analysis, the system of variables representing the influencing factors is established (Table 1).

Table 1 Summary of variables

Variables	Definition	Symbol	Expected direction	Min	Max	Mean	Std.Dev
Dependent Variable							
Housing rents	Housing rents per month (yuan/m ²)	HR		18.22	98.26	34.71	19.86
Built environment							
Mix land use	Mix degree of 6 main land use types (scores)	MLU	-	0.23	1.04	0.71	0.21
Public service level	Density of public service facility (schools, secondary schools, general hospitals, museums, general gymnasiums) (activities/km ²)	PSL	+	0.07	6.30	0.68	1.06
High-rise building	Proportion of high-rise (10 or more floors) residential building (%)	HRB	-	0.00	45.97	14.84	12.27
Air pollution	PM _{2.5} annual average detected value (µg/m ³)	AP	-	25.71	47.03	35.57	4.62
Control variables—Demand and Urban fundamental							
Population growth	The density of permanent population growth (2016–2018) (persons/km ²)	PG	+	0	1606	204	306
Living space	Per capita housing construction area (m ² /person)	LS	-	18.76	44.43	29.06	5.61
Illiterate population	Proportion of illiterate population (%)	IP	-	0.47	5.51	1.92	1.05
Income level	Average wage of employed staff and workers (yuan/year)	IL	+	5082	11,518	7093	1677

Data and Data Sources

Housing rent is measured by monthly rent levels, and the data source is Xitai (<https://www.creprice.cn/rank/index.html>), which is the largest housing database in China. The data were obtained in March 2019.

The sources of the eight variable indicators are as follows: The data on MLU and PSL are from the 2017 point of interest database, which is obtained from Baidu map (<https://map.baidu.com/>). The data on HRB, LS, and IP are from the 1% Population Sample Survey Data of Guangdong in 2015(2015/11). The AP data are from the monitoring station data collected in 2017, which were published by the Ministry of Environmental Protection of China. The PG is from the 2017 and 2019 of Guangdong Statistical Yearbook and the statistical yearbook of each city. IL data are from the 2019 Guangdong Statistical Yearbook and the statistical yearbook of each city (Data for 2018). As there are often delays in the effects of element data on the housing market (Black et al., 2006), it is sensible to use the element data before 2019 for the analysis. To avoid the inversion of causality in the regression model, the dependent variable has a time lag relative to the independent variable (Gu et al., 2020; Wu et al., 2021b). The descriptive statistics are shown in Table 1.

Analytical Model

Combined with the regression analysis and the geodetector technique, the relationships between built environment elements and rent levels and their directions are analyzed, and we furthermore test how the built environment elements cause spatial differences in rents from the perspective of geographic spatial differences.

Spatial Regression Analysis

A regression model is used to identify the rent differences in the PRD, test whether the selection of element indicators is sensible, and check whether the expected directions of influence of the chosen elements on the rent levels are correct. Studies on the factors influencing spatial differences often apply various traditional regression methods, such as ordinary least squares (OLS). With the development of spatial data analysis (e.g., spatial lag model (SLM) or spatial error model (SEM)), spatial regression models can assess spatial effects (Tian et al., 2017). In this study, three regression analysis methods are used to study the factors influencing rent levels and the directions of their effects in the PRD.

OLS is a linear model that is often used to study the linear relations between dependent and independent variables. An OLS model assumes that the variables are independent. In the model, the spatial information of the variables is ignored. The OLS model can be expressed as follows:

$$y_s = \beta X_s + \varepsilon_s, [\varepsilon_s \sim N(0, \delta^2 I)] \quad (1)$$

where $s = 1, \dots, 54$ is the county in the PRD; y_s denotes the rent level in county s ; X_s is a factor influencing rent and is an i -dimensional vector ($i = 1, 2, \dots, 8$), which represents the observed value of each influencing factor i in county s ; β is the i -dimensional column vector of the corresponding regression coefficients of these influencing factor variables; and ε is the error of the model. $\varepsilon_s \sim N(0, \delta^2 I)$ indicates that the error is normally distributed and uniform in variance, e.g., the product of the error matrix and the covariance matrix is 0; I represents the identity matrix. This paper uses the natural logarithm of y_s (independent variable) and the natural logarithms of the independent variables of the X_s vector (i.e., a log-log model) to eliminate the dimensional effect and compare the degrees of influence of the different factors.

The SLM considers the effect of the rental price of one house on the rental prices of other neighboring houses, i.e., the spatial spillover effect. It is a kind of spatial regression model. The SLM can be expressed as follows (Anselin et al., 2006):

$$y_s = \lambda \sum_{j=1}^n W_{sj} y_j + \beta X_s + \varepsilon_s, [\varepsilon_s \sim N(0, \delta^2 I)] \quad (2)$$

where λ is the spatial autoregression coefficient and W_{sj} denotes the diagonal weighting matrix.

In spatial regression analysis, the independent error terms of the models can be spatially autocorrelated. The SEM can evaluate the spatial spillover effects of independent error terms and detect some unknown factors that are spatially correlated. The basic form of the SEM is as follows (Arbia, 2006; Wang et al., 2017a, 2017b):

$$y_s = \rho \sum_{j=1}^n W_{sj} \varphi_j + \beta X_s + \varepsilon_s, [\varepsilon_s \sim N(0, \delta^2 I)] \quad (3)$$

where φ represents the error terms of the spatial autocorrelation and ρ is the spatial autocorrelation coefficient of the error terms.

Geodetector Technique

Regression analysis can only exam the correlations between different variables and the significance of variables. It cannot further assess the degrees of influence of the independent variables on the spatial distribution of these variables. The geodetector technique is a method proposed by Wang et al. (2010) to explore the stratified heterogeneity of variables. The core concept of the geodetector technique is that if the built environment factors x_i have a similar spatial distribution as the housing rent level y , then the built environment element x_i affects the spatial heterogeneity in rents.

$$P = 1 - \frac{1}{N\sigma^2} \sum_{i=1}^n N_i \sigma_i^2 \quad (4)$$

where N is the total number of counties in the PRD, N_i is the number of counties in each subgroup after the independent variables are grouped, and n is the number of independent variable groups. In this study, grouping is conducted manually: First, the element values are ranked, and then the independent variables are grouped into five groups (0%~15%, 15%~35%, 35%~65%, 65%~85%, 85%~100%); σ^2 is the total variance of the rent data; and σ_i^2 is the rent variance of counties in each group. P is the impact intensity, where $P \in [0,1]$. A high p-value indicates that the independent variable has a strong influence on the dependent variable. One of the core strengths and advantages of the geodetector technique is that it does not require the independence or collinearity of the variables (Luo et al., 2016; Wang et al., 2010).

Results and Analysis

Spatial Pattern and Spatial Autocorrelation of Housing Rents

The descriptive cluster statistics of housing rent are presented in Fig. 4. The prices of 20, 25, 35, and 60 RMB/m² are used as the thresholds to group the housing rents into five levels. These levels are represented by 6, 20, 11, 9, and 8 counties, respectively. Figure 5 shows the spatial distribution of housing rent levels in the PRD. The spatial distribution of housing rents can be described as follows: The downtown districts of Shenzhen (Futian, Nanshan, Luohu, Yantian, Bao'an, and Longhua) and those of Guangzhou (Yuexiu and Tianhe) are the centers with high rents, and the rents of other counties decline as the distance to the center increases. The housing rents are generally low in the outlying counties in the PRD. Based on the spatial distribution, Moran's I index is used to measure the spatial correlation of housing rents in the PRD. The finite difference method is used as the valuation basis for the spatial weight matrix, and the threshold distance is 50 km. The Moran's I is

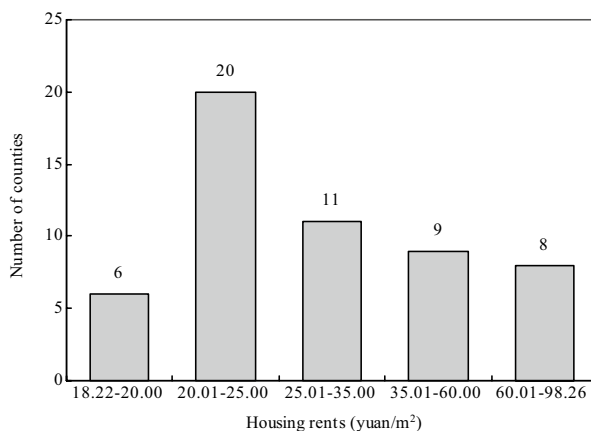


Fig. 4 Descriptive cluster statistics for housing rents in the PRD

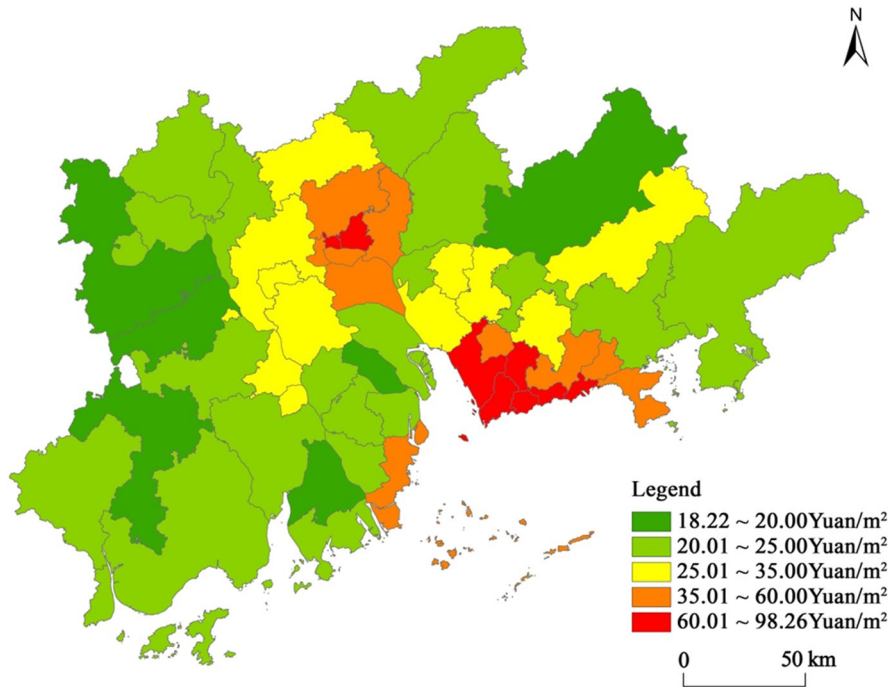


Fig. 5 The pattern of spatial differences in housing rents in the PRD

0.3263 ($p=0.000$; $z=6.8466$). These results indicate that housing rents in the PRD have significant spatial correlation and spatial aggregation.

Effects of the Built Environment on Housing Rents

Regression analysis is the most widely applied approach in studying the factors influencing rent. Among the different regression methods, OLS is the most commonly used method. OLS can be used to evaluate the significance levels and directions of the independent variables' effects on the dependent variables. However, OLS cannot assess the spatial spillover effect between counties. Spatial regression models (including SLM and SEM) are needed to assess such effects. The values of the independent variables and the dependent variables are normalized with log functions. We ran a Lagrange test to verify which regression method is suitable. The results showed that SLM is more appropriate for our study (Lagrange multiplier (lag)=7.7071 ($p=0.0055$); Lagrange multiplier (error)=1.6420 ($p=0.2001$)). We ran three models, including demand, urban fundamentals, and the built environment, to verify the impact of the built environment on housing rent (Table 2).

As shown in model 1, demand and urban fundamentals have a significant impact on housing rent. Model 2 showed that except for the HRBs, all three built environment factors are significant. Model 3 included all the variables, and the

Table 2 Estimation results of the regression models

Variable	Model 1					Model 2					Model 3				
	Coefficient	Std. E	P	VIF		Coefficient	Std. E	P	VIF		Coefficient	Std. E	P	VIF	
Constant	-0.4483	1.2277	0.7150			3.1041***	1.1200	0.0056			2.4058	1.6672	0.1490		
Population growth	0.0416***	0.0154	0.0068	2.6140							0.0732***	0.0215	0.0007	7.3670	
Living space	-0.3190***	0.1071	0.0029	1.2220							-0.3128***	0.1000	0.0018	1.5480	
Illiterate population	-0.2168***	0.0567	0.0001	2.5820							-0.1997***	0.0559	0.0004	3.6780	
Income level	0.3829***	0.1411	0.0067	2.3850							0.2593*	0.1397	0.0635	3.6840	
Mixed land use						-0.1546*	0.0846	0.0678	2.3660		-0.2169***	0.0825	0.0086	4.1010	
Public service level						0.1866***	0.0358	0.0000	2.8510		0.1142***	0.0314	0.0003	4.5210	
High-rise buildings						0.0407	0.0413	0.3249	3.7500		-0.0736**	0.0349	0.0348	4.8110	
Air pollution						-0.4896**	0.2413	0.0425	1.4800		-0.3778*	0.1978	0.0562	2.2240	
W	0.4382	0.0901	0.0000			0.6157	0.0891	0.0000			0.3305	0.0923	0.0003		
	Adjusted R-squared: 0.9057; AIC: -47.7847; Log likelihood: 29.8923					Adjusted R-squared: 0.8776; AIC: -30.7005; Log likelihood: 21.3503					Adjusted R-squared: 0.9270; AIC: -59.393; Log likelihood: 39.6965				

results showed that all eight factors have significant effects on the rent levels. Six factors have significance levels below 0.05. The directions of all eight factors' effects are as expected. Among the four built environment elements studied, MLU, PSL, and HRB influence rent at the 0.05 significance level, while AP does so at the 0.1 level. These values show the strong influences of the built environment on rent levels. For each 1% increase in the degree of MLU, the rent level decreases by 0.2169%. For each 1% increase in the density of public service facilities, the rent level rises by 0.1142%. In addition, each 1% increase in the proportion of high-rise residential buildings leads to a 0.0736% decrease in housing rent. Each 1% increase in $PM_{2.5}$ brings about a 0.3778% drop in rent.

We further used geodetector to assess the four built environment factors' effects on the spatial distribution of rents to determine which of these effects is the strongest. All the variables included in the geodetector technique must be grouped. After sequencing the scores of the factors, the factors were grouped into five levels from high to low (0% ~ 15%, 15% ~ 35%, 35% ~ 65%, 65% ~ 85%, 85% ~ 100%). The spatial distributions are presented in Fig. 6. Following the geodetector principle, the influence degree of each element was calculated (Fig. 7). Among the four built environment elements, AP had the strongest effect and MLU the weakest.

First, AP ($PM_{2.5}$) was found to have a negative impact on the PRD's housing rents. The impact intensity calculated with geodetector is 0.5549, the highest among those of the built environment elements. AP objectively represents the urban environment's cleanliness and influences residents' living choices from the aspects of health and psychology (Chen & Jin, 2019). Generally, AP reflects the industrial structure of a city (Xue et al., 2021). The higher the proportion of high-tech industries, high value-added industries, and clean industries, the more advanced the urban industrial structure, and the lower the degree of urban air pollution (Cheng et al., 2017). It can attract more middle- and high-income residents to move in, making higher rents. It is a key indicator influencing people's general perception of the local environment. These conclusions are in line with the theoretical projections.

Second, HRB has a significant negative correlation with housing rent in the PRD with a 0.5199 P value, showing that its effects on rent differences are second to those of AP. The presence of many HRBs in a residential area often leads to a high floor area ratio, which can negatively affect the built environment's quality. For instance, a high population density can feel too crowded and make people feel depressed (Kearns et al., 2012). From the perspectives of livability and amenities, given similar locations and building qualities, low-rise and low-density buildings are often more popular. From the perspective of supply and demand theory, high-rise buildings provide more housing for rent, which also lowers rents.

Third, there are significant positive correlations between PSL and housing rent, with a P value of 0.4295. The PSL is an important indicator of the built environment; areas with good PSL (such as the downtown districts of Guangzhou and Shenzhen) are more attractive housing areas. These areas have more high-quality public service facilities (such as schools, general hospitals, museums, general gymnasiums), and their rents are correspondingly high. This conclusion agrees with the theoretical prediction.

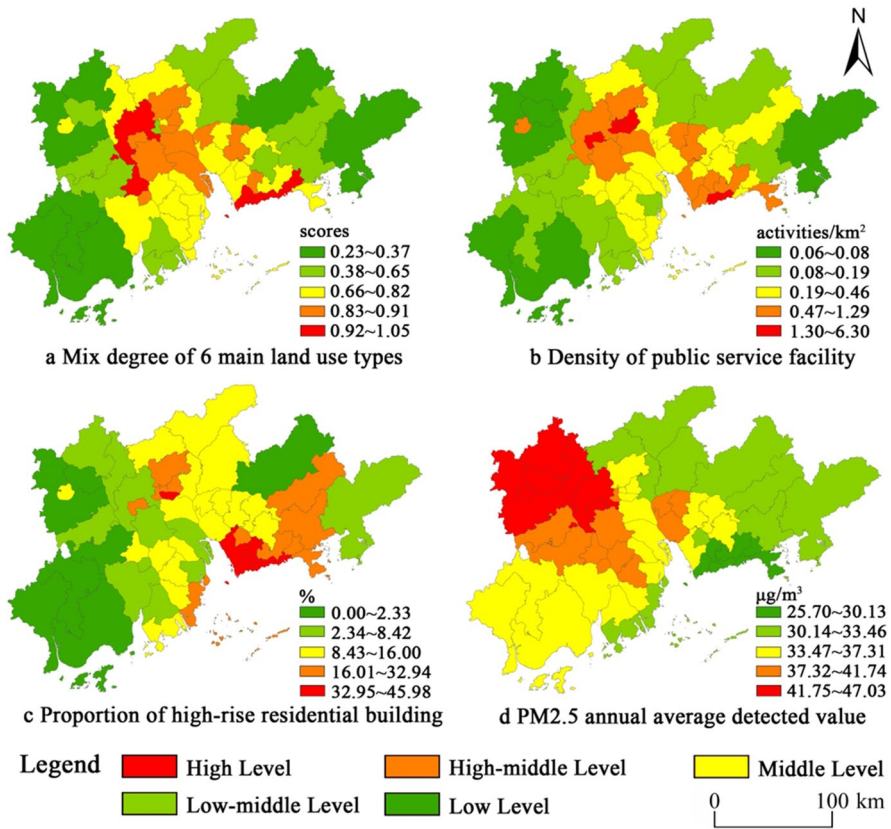


Fig. 6 Map of the four factors of the built environment in relation to housing rents in PRD

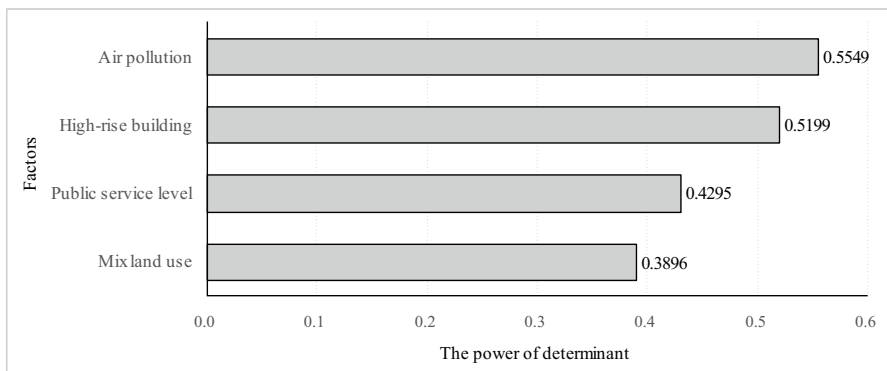


Fig. 7 The power of determinant (P) of the housing rent effects of the four elements of the built environment

Fourth, MLU negatively impacts housing rent. Some studies find that MLU has positive effects on the built environment (Zhang et al., 2012), but the results of this study show that MLU negatively affects rent levels. Consequently, in terms of city livability, MLU can reduce housing amenities and lower rent levels. The PRD produces goods for export worldwide, and a large proportion of its land is for industrial uses. When residential land use is mixed with industrial and transport infrastructure land uses, MLU can negatively affect the built environment and reduce the local livability. However, compared with the effects of other built environment elements, MLU has a weak effect. The geodetector-based calculation indicates that the P of MLU on rent is 0.3896, the lowest among the studied built environment elements.

Fifth, the directions of influence of the four elements representing demand and urban fundamentals (PG, LS, IP, IL) on rent are in line with the theoretical expectations. Except for IL, the p -values of all the indicators are less than 0.01. Thus, apart from built environment elements, the influences of population change, degree of crowding, education level of the residents, and IL on housing rents should be considered. The result also verified the rationality of the four control variables.

Conclusions and Discussion

Conclusions

This paper explains the mechanisms by which the built environment influences housing rent, establishes a framework for assessing the influences of built environment elements on regional housing rents, creates a dataset for studying the housing rents in the 54 counties of the PRD and their influencing factors, and uses SLM to examine the effects of four built environment elements on housing rent. Furthermore, this paper applies geographically weighted regression to assess the intensity of these effects on housing rent. The conclusions are as follows: first, the theoretical part of this paper explains the built environment's effects on spatial differences in the local rent level from the following theoretical perspectives: local public goods theory, the market equilibrium theory of neoclassical economics based on the assumption of rent balance maximization, the research approach of environmental perception, the utility function and hedonic price model, and neo-Marxism and spatial production theory. From the above perspective, in theory, the four elements of the built environment (Mix land use, Public service level, building scale, and Air quality) can affect housing rents. Second, The empirical study based on PRD revealed four elements of the built environment (MLU, PSL, HRB, and AP) have significant effects on housing rent by using SLM. The geodetector technique is used to assess the degree of correlation between built environment elements and housing rents. The results suggest that AP has the strongest impact on rental prices among the four built environment elements, indicating that among these elements, health factors, as represented by AP, significantly influence rent levels.

Discussion

As one of the few papers systematically examining the relationships between local built environments and housing rents, this paper shows strong relationships between the built environment and housing rent both theoretically and empirically.

In theory, this paper constructs a conceptual framework for the impact of built environment on rents. From five perspectives, the four elements of the built environment (mix land use, public service level, building scale, and air quality) have a significant impact on rents. This analyzes at the theoretical level which built environment factors have an impact on rents, and what is the interpretation path for this impact. This will provide a theoretical reference for follow-up similar research.

For case studies, this article used the PRD as a case to find that on the basis of traditional rent-influencing factors, adding built environment factors can explain the spatial differentiation of rents more effectively. The case study proves that the four elements of the built environment significantly affect the housing rent, which responds and validates the theoretical conceptual framework proposed in this article. It also proves the important impact of the built environment on housing rents and gives empirical evidence.

For methodology, this article found that compared with traditional regression models, the data processed by spatial regression methods have a higher degree of fitness and can better reflect the spatial dependence of housing rents. More importantly, this paper reveals the promising prospects of a combination of spatial analysis methods and the geodetector technique in assessing the factors influencing local housing rent.

The study is still insufficient, which need to be further improved in the follow-up research: First, different spatial scales will inevitably affect the analysis results. More detailed research scales (such as towns and streets, communities) can be used for comparison with this research. Second, long-term series data can be used to further verify the theory in the future. Third, different types of people have different understandings and requirements for the built environment. In the future, questionnaire surveys, interviews, experiential observations and other methods can be used to conduct case analysis from the decision-making level of individual housing selection of tenants in order to prove the theoretical framework from the perspective of individual behavior. Fourth, the impact of these built environment factors on residential rents may have spatial heterogeneity effects. Geographic weighted regression can be used to further analyze the spatial difference characteristics of influencing factors in future study.

Policy Implications

This empirical study can have important policymaking implications. Housing rent reflects a city's attractiveness and competitiveness. In recognition of the important influences of the built environment, the municipal and county governments in the PRD should not only consider traditional factors, such as population, income, and

talent, but should also take built environment factors into consideration when formulating urban development policies. To improve the quality of urban living, an urban development strategy oriented toward improving the urban built environment should be formulated. In areas with high rents (for example, the downtown districts of Guangzhou and Shenzhen), the housing development plan should improve the built environment while increasing the supply of rental houses, such as public rental houses and rental homes for highly skilled people. In areas with low rents, public service levels should be improved, pollution should be controlled, a pleasant building-scale environment should be created, and the livability of the region should be enhanced, thereby increasing the attractiveness and competitiveness of the region to the population.

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Declarations

Conflicts of Interest The authors have no conflicts of interest to declare.

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