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ARTICLE

The effects of jobs, amenities, and locations on housing submarkets in Xiamen City, China

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Abstract

Numerous studies have found that jobs, amenities, and location influence housing prices in urban areas. However, there is still a lack of in-depth understanding of the impacts of these factors on various housing submarkets within a city. With the case study of Xiamen, this paper investigates the impacts of jobs, amenities, and location on four housing submarkets, classified by owner-occupied and rental housing, in inner and outer districts. The hedonic model, Chow test, and Tiao-Goldberger test are applied to analyze differentiation in the determinants of housing prices between four submarkets. The results show that all submarkets are influenced by blue-collar jobs (which have negative effects) and seascape (which has a positive impact). Besides, differentiated after submarkets show that school districts and public transportation have a greater influence on owner-occupied markets than on rental markets. A heterogeneity exists between inner-district and outer-district markets. For instance, bus rapid transit (BRT) has a positive effect on housing and rental prices in the outer districts but not in the inner districts. These differences are mainly caused by the disparities of spatial quality, economic development, and public facilities and amenities. The findings have profound implications for decision-making and planning practices.

Keywords Housing prices · Submarkets · Hedonic price model · Accessibility · Owner-occupied housing · Rental housing

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1 Introduction

There is a growing body of literature recognizing that the housing market consists of a series of submarkets. Definitions of housing submarkets may influence the reliability and accuracy of estimated housing prices (Biswas, 2012; Jang & Kang, 2015). Submarkets refer to "groups that are homogenous within and heterogeneous with respect to other groups" (Wu & Sharma, 2012, p.1). Housing submarkets are often defined in terms of geographical areas, relying on existing geographic boundaries, political territories, or spatial partitions based on socioeconomic or environmental characteristics (Alas, 2020; Bourassa et al., 2003). Most of the existing studies have focused on the predictability power of submarket analysis, housing price diffusion patterns at different geographical levels, and the relationships between housing prices and economic fundamentals (Bangura & Lee, 2020). However, the findings are mainly attuned to well-developed contexts, where submarkets have emerged and evolved for several decades. For instance, the majority of housing markets in U.S. metropolitan areas experienced an increase in segregation resulting in the formation of different housing submarkets between 1960 and 1970 (Schnare & Struyk, 1976).

In China, a large number of houses have been constructed in the last 20 years to meet the demand of rapid population growth in cities (Ling & Hui, 2013). The burgeoning market has some distinct features, such as the prevalence of new houses and a movement from welfare housing to houses in the private sector (ibid.). Institutional factors that were inherited from the socialist planned economy and burgeoning market mechanisms have interacted to intensify housing differentiation and segregation (Wei et al., 2020). Chinese society has increasingly become more heterogeneous, which is reflected in the formation of various socioeconomic groups and their different housing choices in diverse locations. For instance, most rural migrants, especially blue-collar workers who have engaged in labor-intensive jobs, live in the so-called "villages in the city" (ViCs) or urban villages in the vicinity of commercial and industrial zones (Lin et al., 2014). Other socioeconomic groups such as pink-collar (who perform service-oriented jobs) and white-collar workers (who engage in professional jobs) also have their own preferences and limitations in housing location choices. These differences in housing location choices of distinctive socio-economic groups could further influence their travel behavior and the degree of accessibility. In turn, the accessibility of jobs, amenities, and location will affect housing prices to varying degrees.

Different socioeconomic groups not only have diverse housing location choices, but also distinctive housing ownership. According to the 2015 Xiamen household travel survey, 88% of citizens with local *hukou* are homeowners, while only 18% of migrants are homeowners. There are many differences between rental housing and owner-occupied housing in terms of flexibility and influential factors. As noted by Donner (2012), the inherent instability of rental housing can increase renters' flexibility in their residential mobility, especially for those having frequent changes of workplaces. Zheng et al., (2016) found that a high-quality school district has a price premium for owner-occupied housing but has no effect on rental housing in Beijing City. More research is required to understand the influence of different amenities and other factors on the submarkets of owner-occupied and rental housing.

In China, urban amenities and facilities have played a more important role in housing prices than in Western countries, because most Chinese cities have experienced rapid urbanization and mass migration without sufficient public facilities, resulting in severe competition for public goods through housing location choices (Feng & Lu, 2013; Yuan et al., 2020). From a comparative study between the inner city and outer suburbs, Li et al., (2019a) found that access to public transportation is less important in the inner city than in the outer suburbs. They also found that public amenities such as banks and hospitals increased housing prices in the inner city while lowering housing prices in the outer suburbs.

There has been increasing interest in the influence of public facilities on submarkets in Chinese cities. Nevertheless, the existing studies have not yet paid sufficient attention to the role of different socioeconomic groups regarding their location choices, access to amenities and jobs, and impact on housing submarkets. Therefore, this study expands the limited existing literature. It develops a conceptual framework for examining the influence of jobs, amenities, and public facilities on housing submarkets. A hedonic price model is applied to examine the relationship between urban amenities, jobs, traffic facilities, and housing and rental prices. This research takes Xiamen City as a case study. Xiamen is a large city located in the southeastern coastal area of China, which has experienced rapid urbanization since the economic reform in the 1980s. The city has a heterogeneous population of approximately 4 million people, very different in socioeconomic and institutional (*hukou*) status. It is a good example to examine the role of housing submarkets in Chinese cities.

This article is structured as follows. In Sect. 2, we review the determinants of housing and rental prices and establish a conceptual framework on housing submarkets. In Sect. 3, we introduce the study area, methods, and variables of the hedonic price model. In Sect. 4, we present the findings of our empirical study in Xiamen. This is followed by our conclusion in Sect. 5.

2 Literature review

2.1 Determinants of housing and rental prices

Hedonic price models establish a functional relationship between housing prices and several attributes that can be divided into three major classes: residential structures, locational attributes, and neighborhood qualities (Hu et al., 2019; Rosen, 1974). One approach to deal with housing submarkets is to compose separated hedonic price models for each submarket (Bourassa et al., 2003; Goodman, 1981).

First, the structural attributes comprise building age, floor levels, and the number of rooms (Jang & Kang, 2015; Saleem et al., 2018). In general, these factors have similar effects on different submarkets. A common finding is that housing and rental prices decrease with building age (Hu et al., 2014; Wen et al., 2014). The number of bedrooms and living rooms has a positive effect on housing and rental prices (Choumert et al., 2014; Pride et al., 2018). In China, high floors often have higher prices due to their better views and less noise (Jiao & Liu, 2010; Li et al., 2016). Whether an apartment is furnished or not also has a significant effect on its price (Tian, 2006).

Second, there are several locational attributes. People are usually willing to pay more money for better access to amenities, therefore locational attributes influence housing prices (Basu & Thibodeau, 1998). These urban amenities include cultural attractions, sports centers, shopping facilities, and hospitals (Huang et al., 2020; Jang & Kang, 2015; Tse & Love, 2000; Wen & Tao, 2015). Access to jobs also influences housing prices (Li et al., 2016), but overall job accessibility may fail to discriminate the differences. Moreover, different economic sectors can have diverse effects on housing prices (Ma, 2002). As noted by Hu et al., (2014), heavy industry has a negative effect on housing prices, while other economic sectors have a positive effect. On the effects of different economic sectors on the rental submarket, not much is known. Furthermore, people are willing to pay more money for greater levels of accessibility to traffic facilities (Competencia, 2008; Tian, 2006; Li et al., 2019b) argued that the influence of traffic facilities varies in different submarkets. They found that proximity to a metro station has greater effects on the suburban market than the inner-city market since public transportation is virtually ubiquitous in the inner city rather than in the suburbs.

Third, neighborhood variables play a pivotal role in influencing housing prices. Many studies have shown that school quality can have a positive effect on housing prices, especially in Chinese cities (Agarwal et al., 2016; Haurin & Brasington, 1996; Wen et al., 2015), but no effect on rents (Zheng et al., 2016), since the enrollment of the primary school is only bundled with homeownership in China. Previous research has also shown that attractive seascapes and landscapes, such as parks, green spaces, rivers, and lakes, have a positive effect on housing prices (Chou et al., 2015; Nilsson, 2015; Yang et al., 2016). Lastly, evidence shows that housing prices can be lower in those neighborhoods close to the informal settlements of urban villages (Chen & Jim, 2010; Song & Zenou, 2012). So far, however, on the effects of different urban villages on the rental submarket not much is known.

Although a growing body of literature has studied the relationships between housing prices and several attributes, many existing studies have failed to identify the differences in determinants among housing submarkets. This study will bridge the gap by examining the differences between the determinants of housing and rental prices in various submarkets in Xiamen City. For this, the housing market has been subdivided into housing submarkets that differentiate in terms of owner-occupied housing and rental housing located in inner and outer districts.

2.2 Conceptual framework

Understanding housing market variations within urban regions could be traced back to Alonso's theory of bid rents (Alonso, 1964). However, subsequent work showed that the structure of real-world cities is much more complex. Certain areas may trigger different social and physical development patterns in a historical period, which are then reflected in the subsequent characteristics of these areas through the process of "path dependence" (Bramley et al., 2008). The hedonic price model, which is the most commonly used statistical model of house price or rent changes, shows that housing and rental prices depend foremost on their internal and external characteristics (Lisi, 2019). Nevertheless, buyers may be willing to switch to other types of housing if they cannot get their first choice. This suggests that different parts of the market may operate semi-independently even within an urban area, resulting in housing submarkets (Bramley et al., 2008).

The specification of housing submarkets can be done in several ways, one of which is a spatial specification emphasizing a predefined geographic area (e.g., inner/outer city) along with people's homogenous choice preferences (Gabriel & Wolch, 1984; Xiao, 2017). Most studies have focused on owner-occupied housing (e.g. Bangura & Lee 2020; Keskin & Watkins, 2017), while some studies have combined owner-occupied and rental housing (Halket & Pignatti, 2015; Jun & Namgung, 2018). For instance, Halket & Pignatti (2015) defined a submarket as "all housing for rent or sale within a zip code with the same number of bed-

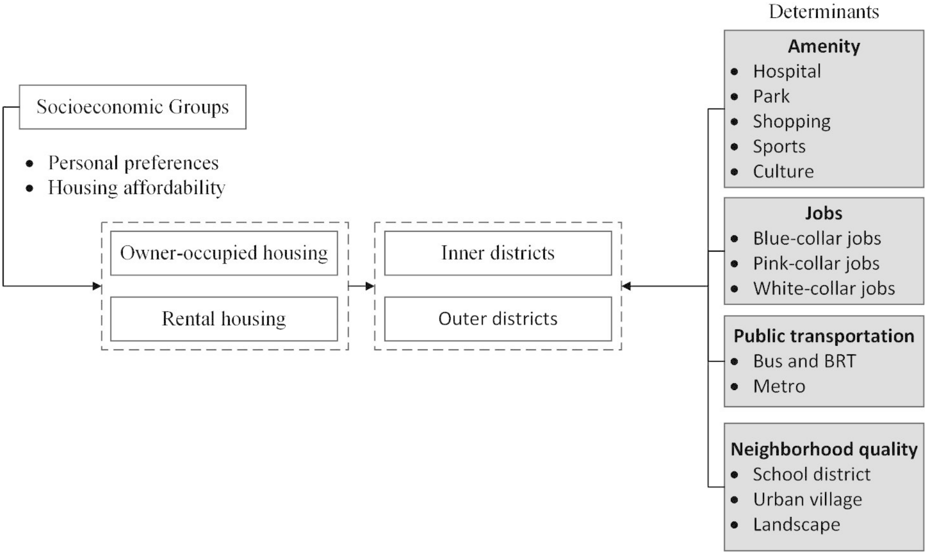

Fig. 1 Conceptual framework for housing submarkets

rooms." Moreover, the housing submarket could be divided based on the characteristics of housing structures, such as floor area and lot size (Halket & Pignatti, 2015; Watkins, 2001). Some scholars have divided submarkets by race (Palm, 1978) or household income (Palm, 1978; Schnare & Struyk, 1976), which has been criticized by Watkins (2001) for their unsatisfactory results. A broader classification has been developed by Alkay (2008), who linked household income with geographical location. Alkay (2008) did choose old inner-city housing areas to represent middle-income groups, new block housing areas to represent high-income groups, and squatter settlements to represent low-income groups. The results show that there are significant price differences between the three submarkets. Another method is to classify submarkets by statistical analysis, such as factor analysis and cluster analysis. Although some scholars argue that submarkets generated by statistical analysis are better than an a priori classification, the improvement is not obvious (Bourassa et al., 1999).

In our analysis, we use a priori classification rather than a statistical analysis. Many scholars have provided evidence for the existence of submarkets (Bourassa et al., 1999). Similar to Alkay (2008), we link socio-economic characteristics to a predefined geographic area and study the determinants of owner-occupied and rental markets separately (Fig. 1). The main reason is that many studies have proven that the segmentation of the housing market is related to the behavior of people who adopt very different geographic strategies (Cox & Hurtubia, 2020; Watkins, 2001). For instance, there exists a considerable difference between locals and migrants in choosing within and between the owner-occupied and rental submarket. Due to institutional barriers like their non-urban *hukou* and their low-income status, the majority of rural migrants within the city are not able to purchase commodity housing and as a consequence lives in private rental housing or dorms provided by employers (Liu et al., 2017). In Xiamen, more than 90% of locals are homeowners, while less than 15% of migrants are homeowners (Li et al., 2021), indicating that locals and migrants choose the owner-occupied housing market and rental market respectively. Additionally,

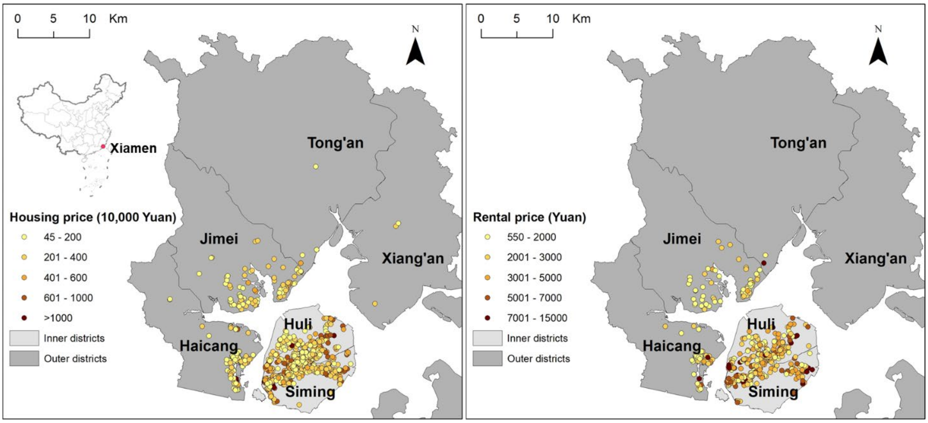

Fig. 2 Distribution of housing and rental prices in Xiamen

geographical factors are an important factor that affects submarket prices, and spatial preference and limitations exist between different socio-economic groups. With the rapid industrialization and urbanization in China, new housing markets have emerged in the suburbs of many cities. Most new housing is developed on what used to be farmland, resulting in a lack of urban services for at least some time. Accordingly, a predefined geographic area along with people's homogenous choice preferences can be classified as inner and outer districts. According to the 2015 Xiamen household travel survey, more than 50% of pink-collar and white-collar locals lived in the inner districts with higher accessibility while only 30% of blue-collar locals lived there. This suggests that different socioeconomic groups have references or limitations in selecting specific submarkets, which will result in different degrees of accessibility due to varied geographical characteristics. Therefore, our model includes several key factors, including the mentioned three types of jobs, amenities (e.g. hospital, parks, shops, sports), transport facilities (e.g. bus, metro), and neighborhood qualities (e.g. school district, urban villages, landscape). These factors can affect housing selling and renting prices in the inner and outer districts.

A considerable number of studies have proven that a separate evaluation of potential submarket models has a superior predictive power than an overall market evaluation (Chen et al., 2009; Leishman, 2009). Therefore, we evaluate the submarkets separately and examine how each determinant diversely affects them. The evaluation results in turn reveal the advantages and disadvantages of different groups regarding housing choices. For some variables, raising housing prices or rents means that the corresponding low-income groups are at a disadvantage in competing for these resources.

3 Methodology

3.1 Study area and data

Xiamen City is located in the southeastern coastal area of China. The urbanized area of the city has spread from two inner districts (Siming and Huli) in Xiamen Island to Xiamen's four mainland/outer districts, namely of Haicang, Jimei, Tong'an, and Xiang'an. In 2017, the permanent population of Xiamen reached 4 million, 50% of whom were migrants.

Multiple datasets were collected and used in this research. Housing transaction data were collected from a widely used housing sale and rental service platform in October 2018 (https://xm.lianjia.com/). The original data included housing sales data from 2015 to 2018 and housing rental data from 2016 to 2018. Considering that the metro started operation on the last day of 2017, we only selected 2016 and 2017 as the research period to narrow the difference caused by its operation. We added dummy variables of years to control the influence of time on housing prices. In total, data on 2,735 housing unit sales (1,702 in the inner districts and 1,033 in the outer districts) and 1,378 housing unit rentals (1,085 in the inner districts and 293 in the outer districts) were selected (Fig. 2). Another dataset was provided by the Xiamen Municipal Bureau of Commerce, including 65,891 company records and employment data of 2,026,217 jobs. Geographic information on amenities including culture, entertainment, exercise, hospitals, shopping, and parks—was obtained from an open data platform - Baidu API. In addition, high-quality school district data were collected from the "Xiamen Bianmin[1] Network" (http://m.xmbmw123.com/).

3.2 Methods

In line with previous studies, we applied a hedonic price model to examine the relationship between urban amenities, jobs, traffic facilities, and housing and rental prices. The hedonic price function (HPF) for our ordinary least squares (OLS) model can be formally expressed as:

$$\mathrm{LN}\,(\mathrm{P}) = \alpha + \beta \mathrm{S} + \gamma \mathrm{L} + \eta \mathrm{N} + \theta \mathrm{T} + \epsilon \tag{1}$$

where $\mathrm{LN}\,(\mathrm{P})$ is the natural logarithm of the transaction price; S, L, N, and T represent structural (S), locational (L), neighborhood (N), and transaction time (T) variables; α, β, γ, η, and θ are the corresponding parameters; and ε is the random error term.

However, the traditional OLS model has a limitation, i.e. it neglects spatial autocorrelation. In order to test spatial autocorrelation, we calculated spatial weight. To build the spatial weights matrix, we created neighbors for each housing location beforehand (Bivand, 2017). We built graph-based neighbors, choosing 4 nearest neighbors for each location to build the spatial matrix.

The Moran's I values of the four submarkets range from 0.150 to 0.283 at significant level, indicating the existence of spatial autocorrelation. In order to select the alternative models, we conducted Lagrange-multiplier (LM) test. The result shows that there is significant spatial autocorrelation, and reveals that it's better to choose the spatial error model (SEM) for inner- and outer-district owner-occupied housing and inner-district rental housing, and a spatial lag model (SLM) for outer-district rental housing.

SEM model can be presented as:

$$\mathrm{LN}\,(\mathrm{P}) = \beta \mathrm{S} + \gamma \mathrm{L} + \eta \mathrm{N} + \theta \mathrm{T} + \mu \text{ where } \mu = \delta W \mu + \epsilon \tag{2}$$

[1] This website provides some information services, such as household registration, enrollment, entrepreneurship, etc.

where μ is a n $\times$ 1 vector of error term; W is the standardized n $\times$ n weight matrix; δ is a spatial autoregressive parameter.

SLM model can be presented as:

$$\mathrm{LN}\,(\mathrm{P}) = \alpha + \rho \mathrm{WP} + \beta \mathrm{S} + \gamma \mathrm{L} + \eta \mathrm{N} + \theta \mathrm{T} + \epsilon \tag{3}$$

Where WP represents the spatial lag of observations with n $\times$ n weight matrix W, and ρ is its corresponding parameter.

To explore statistical differences between subgroup regressions, a Chow-test was employed. The Chow F-statistic can be presented as:

$$\mathrm{F} = \frac{SSR_c - (SSR_1 + SSR_2)}{(SSR_1 + SSR_2)} \times \frac{(N_1 + N_2 - 2k)}{k} \tag{4}$$

Where $SSR_{1,} SSR_{2,}$ and SSR_c represent the sum of squared residuals of the first model, the second model, and the combined model, respectively. N_1 and N_2 are the number of observations of the first model and the second model. K denotes the number of parameters.

To explore statistical differences between the coefficients of the subgroup regressions, a Tiao-Goldberger test was employed. The formula can be presented as:

$$F_{TG} = \frac{\sum_{j=1}^{L} \frac{(\widehat{b}_{ij} - \overline{b}_i)^2}{P_{ij}}}{\sum_{j=1}^{L} SSR_j} \times \frac{\sum_{j=1}^{L} (N_j - k_j)}{L - 1} \tag{5}$$

Where:

$$\overline{b}_i = \frac{\sum_{j=1}^{L} \frac{\widehat{b}_{ij}}{P_{ij}}}{\sum_{j=1}^{L} \frac{1}{P_{ij}}} \tag{6}$$

with L is the number of models being compared; $\widehat{b}_{ij}$ represent the OLS coefficient of parameter *i* in model *j*; P_{ij} means the diagonal element of the *i*th parameter of $(X^T X)_j^{-1}$; SSR_i, N_i, $and k_i$ represent the sum of squared residuals, number of observations, and the number of parameters of the model j, respectively.

3.3 Variables

The description of variables is shown in Table 1. In this study, we adopted three main categories of independent variables: residential structure, locational attributes, and neighborhood quality. In general, area, interior, total floor area, number of bedrooms, number of living rooms positively impact housing and rental prices while building age negatively impact housing and rental prices (Li et al., 2019a; Wen et al., 2014), and we selected those variables as our structural variables. As our data covers a period from 2016 to 2017, we added a time dummy variable to control temporal effects, which was adopted by many previous studies (Agarwal et al., 2016; Kang, 2019).

Table 1 Description of variables

Variable	Description	Mean/Proportion			
		Owner-occupied housing		Rental housing	
		Inner districts	Outer districts	Inner districts	Outer districts
Dependent variable					
Ln_THP	Logarithm of total housing price (unit: 1,000 Yuan); Logarithm of total rental price (unit: Yuan)	7.97	7.80	7.92	7.59
Structural variables					
Area	Floor area (unit: m^2)	86.05	95.98	73.61	88.82
Interior	Simply furnished (reference)	31.9%	27.2%	23.0%	18.8%
	Rough housing;	4.1%	12.4%	0.5%	1.3%
	Well-furnished house;	39.2%	43.6%	12.2%	9.6%
	Other;	24.8%	16.8%	64.3%	70.3%
Total floor	Low-rise building: Total number of floors 1–3;	0.3%	0.5%	0.3%	2.9%
	Multistory building: Total number of floors 4–6;	11.5%	11.1%	13.8%	17.3%
	Medium-high building: Total number of floors 7–9 (reference);	28.4%	14.5%	21.3%	19.2%
	High-rise building: Total number of floors > 10;	59.7%	73.8%	64.6%	60.7%
Bedroom	Number of bedrooms	2.28	2.53	1.93	2.25
Living room	Number of living rooms	1.40	1.72	1.13	1.49
Building age	Age of apartment building	14.21	8.63	14.57	11.19
Locational variables					
Culture	Number of libraries culture centers within 1 km	1.91	1.45	1.82	2.21
Sports	Number of sports centers within 1 km	0.35	0.47	0.23	0.34
Hospital	Number of hospitals within 1 km	2.42	0.74	2.42	1.33
Shopping	Number of shopping facilities within 1 km	11.47	4.20	11.94	5.28
Park	Number of district-level parks within 1 km	1.04	0.84	1.02	1.21
Blue-collar jobs	Number of blue-collar jobs within 1 km (unit: 10,000)	0.96	0.39	1.01	0.57
Pink-collar jobs	Number of pink-collar jobs within 1 km (unit: 10,000)	2.05	0.20	2.21	0.33
White-collar jobs	Number of white-collar jobs within 1 km (unit: 10,000)	0.55	0.05	0.57	0.09
Bus stops	Number of bus stops within 1 km	21.64	11.17	21.36	13.89
BRT	Dummy variable: 1 when there is a BRT station within 1 km, 0 = otherwise	0.53	0.14	0.50	0.12
Metro	Dummy variable: 1 = if there is a planned metro station within 1 km, 0 = otherwise	0.76	0.44	0.79	0.51
Neighborhood variables					

Table 1 (continued)

Variable	Description	Mean/Proportion			
River	Dummy variable: 1 = if there is a river or lake within 300 m, 0 = otherwise	0.12	0.00	0.10	0.00
Seascape	Dummy variable: 1 = if the sea is within 300 m, 0 = otherwise	0.03	0.19	0.03	0.13
School district	Dummy variable: 1 = if it is in a high-quality school district, 0 = otherwise	0.25	0.12	0.24	0.27
Urban villages	Dummy variable: 1 = if there is a urban village within 100 m, 0 = otherwise	0.06	0.12	0.08	0.16

Consistent with existing literature, we selected culture, sports, hospitals, shopping, and parks as our locational variables. In general, locational attributes positively influence housing prices, because people are willing to pay extra money for better accessibility and amenities (Basu & Thibodeau, 1998). However, the influence may vary by sub-market and by city (Li et al., 2019a). In terms of job accessibility, we differentiated between different economic sectors. In line with Fan et al., (2014), we divided economic sectors into three levels: blue-collar jobs, pink-collar jobs, and white-collar jobs. The blue-collar jobs are expected to have a negative effect on housing and rental prices while the other two categories of jobs are expected to have a positive effect on housing and rental prices (Hu et al., 2014). Traffic facilities include bus stops, bus rapid transit (BRT), and the metro. Xiamen's BRT began to operate in 2008 and is considered as the first elevated BRT network in China. The first metro line began to be operated on 31 December 1, 2017. Since the selected housing price data is the data of 2016 and 2017, there are no operational lines during this data period. As Li et al., (2019a, 2019b) noted, traffic facilities are expected to have greater effects on the outer districts' market than the inner districts' market. Consistent with previous studies, we chose 1 km as the threshold distance of the locational variables, which is regarded as walking distance (Wen & Tao, 2015; Yuan et al., 2020).

Neighborhood variables like school quality (Agarwal et al., 2016; Wen et al., 2015) and attractive landscapes (Bolitzer & Netusil, 2000; Wen et al., 2015; Yang et al., 2016) also play a pivotal role in influencing housing prices. In Xiamen, a child must attend the primary school in his or her district. We chose 21 high-quality school districts, including 14 provincial-level demonstration primary schools and 7 primary schools, which also provide access to high-level secondary schools. School quality is expected to have a positive impact on housing prices and no effect on rents. In terms of landscape variables, we included all rivers, lakes, and bays to test their effects on housing prices. We chose a 300-meter buffer as the threshold for rivers, lakes, and bays. Because in China, housing within 300 m of the sea is considered as the first-line sea view housing[2] with excellent sea views. In addition, evidence shows that housing values can be lower in the proximity of urban villages. Although our dataset doesn't include the housing market within urban villages which is often informal and lacks precise statistical data, it considers the presence of urban villages in the vicinity of other housing markets. Consistent with Liu et al., (2017), we used a 100-meter buffer as the threshold because we intended to examine the impact of nearby urban villages on housing prices.

[2] Sea view housing (i.e. haijingfang) is a real estate term in China, usually used to attract consumers. According to the location of the beach, it is divided into first-line ocean view housing (less than 300 m), second-line ocean view housing (between 300 and 800 m), and third-line ocean view housing (more than 800 m).

Descriptive statistics show the characteristics of different submarkets are different. In general, the accessibility of amenities and public transportation is greater in the inner districts than in the outer districts. Regarding neighborhood variables, the inner districts enjoy better river views and high-quality school districts than the outer districts, while the outer districts enjoy better sea views than the inner area but have more urban villages nearby.

4 Results

Owner-occupied housing price and rental housing price in the inner districts are 26.9% and 39.1% higher than those in the outer districts. The estimated results for each submarket are shown in Table 2.

Regarding structural variables, our findings are similar to that of previous studies (Hu et al., 2014; Wen et al., 2014), i.e. furnished housing, more bedrooms, more living rooms, larger areas, and high-rise buildings increase housing and rental prices, while an increase in building age lowers both prices.

In terms of our focus variables, the result shows the effect of locational and neighborhood variables on housing and rental prices. The Chow tests were conducted to test whether the regression slopes of different submarkets were statistically significant, and the results show that heterogeneity exists (Table 3).

In addition, the Tiao-Goldberger F-test was performed to test which coefficient in the submarkets causes the difference between the submarkets (Table 4). To explore the differences between owner-occupied vs. rental markets as well as between inner-district vs. outer-district housing markets, we integrated the inner- and outer-district market sample in the former case, and owner-occupied and rental market samples in the latter case (Fig. 3). We explain the differences in the following sections.

4.1 Diversities: owner-occupied housing and rental housing

The findings show that sports, blue-collar jobs, pink-collar jobs, and bus stops have a great influence on the owner-occupied market but have little impact on the rental market. Sports facilities have a positive effect on housing prices, but no effect on the rents. This is because most of the sports centers in our sample are youth sports centers, which is probably related to the quality of the school district. Blue-collar jobs negatively impact housing and rental prices, but they have a bigger impact on house prices than rents. Pink collar jobs have a different impact on owner-occupied submarkets and rental submarkets. It should be pointed out that the Tiao-Goldberger F-test was carried out based on OLS rather than SEM or SLM model. If spatial autocorrelation is taken into account, there may be no difference between the two submarkets. Regarding public transportation, bus stops have a positive effect on housing sale prices, but not on house rents. Since homeowners commute longer distances than renters (Li et al., 2021), accessibility to bus stations is more important to the homeowners.

Table 2 Regression results of OLS, SEM, and SLM

	Owner-occupied housing				Rental housing			
	Inner districts		**Outer districts**		**Inner districts**		**Outer districts**	
	OLS	SEM	OLS	SEM	OLS	SEM	OLS	SLM
Area	0.008***	0.008***	0.007***	0.008***	0.007***	0.006***	0.004***	0.004***
Interior (ref: simply furnished)								
Well-furnished	0.044**	0.047***	0.037**	0.043***	0.131***	0.117***	0.121*	0.104*
Other	-0.017	0.018	0.016	0.021	0.034*	0.038**	0.005	0.003
Rough housing	0.023	0.065*	-0.013	-0.016	-0.135	-0.125	-0.810***	-0.760***
Total floor (ref: Medium-high building)								
High-rise buildings	0.080***	0.104***	0.162***	0.188***	0.047**	0.041	0.071	0.068
Multistory building	0.042*	0.049**	0.023	0.01	-0.007	-0.006	0.097*	0.083*
Low-rise building	-0.450***	-0.308***	-0.024	-0.075	0.041	0.059	0.168	0.133
Bedroom	0.097***	0.091***	0.094***	0.065***	0.073***	0.084***	0.092***	0.085***
Livingroom	0.156***	0.146***	0.131***	0.137***	0.179***	0.175***	0.151***	0.162***
Building Age	-0.006***	-0.007***	-0.007***	-0.006***	-0.008***	-0.008***	-0.0004	-0.001
Culture	0.016***	0.010*	0.021***	0.019***	0.009	0.005	0.044***	0.041***
Sports	0.024	0.025	0.056**	0.063***	0.007	-0.0002	-0.034	-0.018
Hospital	-0.017***	-0.011**	-0.01	-0.012	-0.011**	-0.011*	0.009	0.007
Shopping	-0.008***	-0.006***	0.007*	0.001	-0.002	-0.002	0.0002	0.001
Park	0.01	-0.003	-0.054***	-0.056***	-0.015	-0.016	0.001	-0.001
Blue-collar jobs		-0.046***	-0.079***	-0.109***	-0.039***	-0.039***	-0.081***	-0.053*
Pink-collar jobs	0.029**	0.011	0.083	0.169	-0.002	-0.004	0.258	0.198
White-collar jobs	0.051	0.107**	0.011	0.355	0.159***	0.163***	-1.601**	-1.315**
Year 2017	0.268***	0.198***	0.252***	0.144***	-0.054*	-0.060*	0.055	0.052
Bus stops	0.005***	0.003	0.009***	0.008**	-0.001	0.0002	-0.004	-0.006
BRT	-0.066***	-0.097***	0.071**	0.075*	-0.026	-0.029	0.288***	0.286***
Metro (ref: No)	0.138***	0.090***	0.090***	0.156***	0.060**	0.062**	-0.103**	-0.089**
River	-0.013	0.024	-0.08	-0.117	-0.017	-0.024		
Seascape	0.190***	0.135**	0.054***	0.070***	0.163**	0.148**	0.141***	0.125***
School district	0.096***	0.102***	-0.048	-0.053*	-0.0002	-0.001	-0.005	0.017
Urban villages	0.02	0.028	-0.039*	-0.037*	-0.03	-0.047	-0.035	-0.031
Constant	4.317***	4.444***	4.000***	4.006***	7.182***	7.169***	6.746***	5.596***
R2	0.79		0.837		0.78		0.747	
Adjusted R2	0.786		0.833		0.774		0.724	
Log Likelihood		-215.568		286.676		9.151		4.344
AIC	624.544	489.135	-324.077	-515.351	91.645	39.699	53.971	47.311

Note: *p < 0.1; **p < 0.05; ***p < 0.01

Table 3 Chow test results

Segmentation Physical		Chow
Owner-occupied housing	Inner districts with Outer districts	6.564 ***
Rental housing	Inner districts with Outer districts	6.665***
Inner districts	Owner-occupied housing with Rental housing	1220.639***
Outer districts	Owner-occupied housing with Rental housing	658.671***

Note: *p<0.1; **p<0.05; ***p<0.01

Table 4 Tiao-Goldberger test

		Owner-occupied housing VS Rental housing	Inner districts VS Outer districts
	Culture	4.661***	5.281***
8	Sports	3.926***	0.188
9	Hospital	0.077	3.231***
10	Shopping	15.711***	14.613***
11	Park	2.531***	14.349***
12	Blue-collar jobs	7.240***	1.106
13	Pink-collar jobs	4.341***	0.355
14	White-collar jobs	16.828***	4.655***
15	Year 2017	67.143***	7.813***
16	Bus stops	6.166***	0.107
17	BRT	1.893***	25.173***
	Metro (ref: No)	13.626***	11.662***
	River	0.834	0.041
	Seascape	0.569	7.131***
	School district	10.293***	7.954***
	Urban villages	1.759**	2.707***
	Constant	67.079***	7.759***

Note: *p<0.1; **p<0.05; ***p<0.01

4.2 Diversities: inner district and outer district

The results show that some variables including hospital and seascape have different effects on inner- and outer-district markets. In the inner districts, hospitals have a negative effect on housing markets, since they can cause nuisance (Huang, 2017), but have no impact on the housing market in the outer districts. A possible explanation is that in the outer-district hospitals are not located in close proximity to residential areas and will have less impact on living conditions. Seascape positively impact housing and rental prices in all submarkets, but the impact was greater in the inner districts than in the outer districts. The higher impact on the inner city may be due to the development of yacht marinas in the inner districts and the development of many high-end villas around the yacht marina.

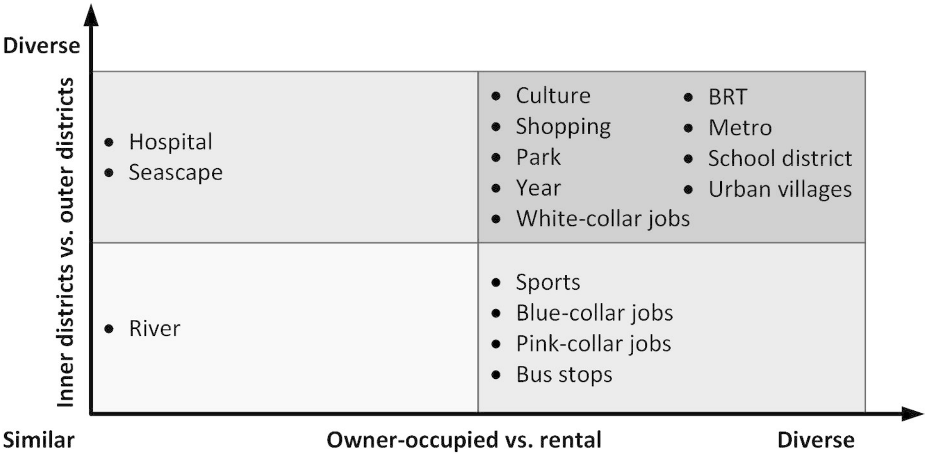

Fig. 3 Similarity and diversity between housing submarkets

4.3 Diversities: across all submarkets

The results show that the influence of most variables—including culture, shopping, park, year, white-collar jobs, BRT, metro, school district, and urban villages—is different in each submarket. Cultural facilities such as libraries and cultural centers have no impact on the inner-district rental market but have a positive impact on the other three submarkets. Contrary to our expectations, shopping facilities have a negative impact on housing prices in the inner districts. This may be related to our selection of variables, in which retail and convenience stores are part of the shopping variable. Jang & Kang (2015) found that compared with shopping centers, the impact of supermarkets and convenience stores on housing prices is not significant. In addition, district-level parks have a negative impact on sale prices in the outer districts. Yang et al., (2016) found that there is a significant negative correlation between district-level green spaces and sale prices since the reservation value of district-level public parks is higher than their use-value. In the outer districts, large parks tend to be located in areas with low population density and underdeveloped facilities, thereby having a negative impact on sale prices. In terms of transaction time, although housing prices were higher in 2017 than in 2016, rents were lower, especially in the inner districts. This suggests that sale prices and rental prices are inconsistent over time. White-collar jobs have a significant positive impact on housing sales and rental prices in the inner city, but do not affect sales prices in the outer districts, or even negatively affect rental prices in the outer districts. This negative effect may be caused by the fact that most white-collar jobs are mainly concentrated in the old areas of the outer districts, where the environment and buildings are relatively dilapidated which is lowering rental prices. BRT negatively impacts inner-district housing prices but positively impacts outer-district housing prices and rents. Regarding inner districts, public transportation facilities are already well developed, which leads to the lack of attractiveness of BRT. In contrast, BRT foremost enables people living in the outer districts to reach working places and services in the inner districts more efficiently. (Planned) metro stations negatively impact the outer-districts rental market, but positively impact the other three submarkets. This may be because, for many short-term tenants, metro construction has no impact on their current lives. High-quality school district increases the housing prices in the inner district but not the rental prices. This is because only the children of homeowners can enroll in that particular school district, not of renters. Nevertheless, the high-quality school district in the outer districts negatively affects housing prices. In the outer districts, there are two high-quality school districts which are provincial-level demonstrations[3] of primary school districts. However, their surrounding environment is dilapidated and there is a lack of public facilities and amenities which is dominantly affecting the housing prices (Wang & Chen, 2020). In addition, adjacency to urban villages lowers sale prices in the outer districts but does not affect the other three submarkets. This may be because most urban villages in the inner districts are undergoing redevelopment and demolition, and the redevelopment has the potential to increase rather than reduce sale prices in the vicinity of urban villages (Liu et al., 2017). Regarding rental markets, it is possible that renters pay more attention to the advantages of accessibility while giving less attention to the living environment inside urban villages due to the short-term rental.

5 Conclusion

Although housing submarkets have attracted increasing research interest, few studies have taken into account distinct socioeconomic groups' housing choices, accessibility to amenities and jobs as well as their impact on different submarkets. This research is an attempt to widen the scope. It examines the influence of jobs, amenities, public facilities, and neighborhood qualities on four distinctive housing submarkets (owner-occupied housing, rental housing, the inner districts, and the outer districts) for three different socioeconomic groups (white-collar, pink-collar, and blue-collar jobs) in Xiamen City. It gains insights into the determinants of housing and rental prices in inner- and outer-district submarkets. The Chow test and the Tiao-Goldberger test show that there are significant differences between these four submarkets. The Tiao-Goldberger test identifies the difference between positive and negative impacts and the degree of impact, while we pay more attention to the difference between positive and negative impacts. We draw the following three conclusions according to the results of the hedonic model.

First, pollution and noise nuisance caused by blue-collar jobs can reduce housing and rental prices throughout the city, which is consistent with the finding of previous studies that heavy industry has a negative effect on sale prices (Hu et al., 2014). Seascape has a significant positive impact on housing prices and rents, although the degree of impact varies. Second, bus stops, school districts, and various amenities have a substantial influence on owner-occupied markets but not on rental markets. Compared to renters, homeowners commute longer distances and compete for more educational resources, public transportation, and amenities (Zheng et al., 2016). Third, heterogeneity exists between inner-district and outer-district markets. These differences are mainly caused by spatial, economic, and historical differences. The inner districts are the commercial, cultural, historical, and geographic heart of Xiamen City, with high-quality jobs and urban services as well as dense population and construction. In contrast, the outer districts are characterized by a lack of public facili-

[3] We select the provincial-level demonstration of primary school as the high-quality school districts and the Children living in newly built communities may also be assigned to other level of high-quality school districts, which is ignored in our analysis.

ties and amenities, sparse high-quality jobs and urban services, lesser population density, and more green spaces. As a consequence, the negative impact caused by hospitals, such as traffic congestion, noise nuisance, and air pollution, are mainly impacted on high-density inner districts rather than on low-density outer districts. There is also a positive effect of high-quality white-collar jobs in the inner districts but not in the outer districts. Additionally, an efficient transportation system of BRT helps those residents living in the suburbs to commute to their working places (e.g. service sectors) in the city center and thereby plays an influential role in housing and rental prices in the outer districts.

These findings increase our understanding of heterogeneity across distinctive housing submarkets which are occupied by different socioeconomic groups. As 85% of migrants are renters (Li et al., 2021), their housing behavior is mainly influenced by the rental market. Rental prices are less affected by the accessibility of public services and more affected by employment, labor market, and wages, implying that the most substantial barrier to trapping low-income renters is access to high-paying jobs (Li et al., 2019a). In contrast, the housing behavior of local residents (more than 90% are homeowners) is mainly affected by the housing sales market. Housing prices are mainly affected by the accessibility of public services, educational resources, and public transportation, suggesting that the main barrier to trapping low-income homeowners is access to these resources. These differences between migrant and local residents also provide evidence for the added value of identifying distinctive submarkets in the analysis of the housing market.

Furthermore, these findings also provide a basis for housing market development and spatial planning. As low-income houses in urban villages in the inner cities continue to be demolished and upgraded—which raises housing prices (Liang et al., 2019)—the rent burden of migrant workers in the inner districts will increase. To lighten their burden, the government should broaden the supply of rental housing, including allowing vacant industrial plants, office buildings, and other non-residential buildings to be converted into rental housing. Moreover, the government should include low-income migrants in the housing system. Additionally, for low-income locals, government-subsidized affordable housing—which is generally built in the outer districts—is their first choice. In the outer districts, new planning strategies could be developed to improve the public transportation system and urban public service facilities to improve the quality of life of the low-income population. Furthermore, the suburbanization of the population must be accompanied by the suburbanization of employment and service facilities. Local governments and decision-makers could balance the urban development by improving the suburban transportation environment and public service facilities and decentralizing employment (Li et al., 2019b).

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References

Agarwal, S., Rengarajan, S., Sing, T. F., & Yang, Y. (2016). School allocation rules and housing prices: A quasi-experiment with school relocation events in Singapore. *Regional Science and Urban Economics*, *58*, 42–56. https://doi.org/10.1016/j.regsciurbeco.2016.02.003

Alas, B. (2020). A multilevel analysis of housing submarkets defined by the municipal boundaries and by the street connections in the metropolitan area: Istanbul. *Journal of Housing and the Built Environment*, *35*(4), 1201–1217. https://doi.org/10.1007/s10901-020-09735-7

Alkay, E. (2008). Housing Submarkets in Istanbul. *International Real Estate Review*, *11*(1), 113–127

Alonso, W. (1964). *Location and Land Use. Toward a General Theory of Land Rent*. Cambridge: Harvard University Press

Bangura, M., & Lee, C. L. (2020). House price diffusion of housing submarkets in Greater Sydney. *Housing Studies*, *35*(6), 1110–1141. https://doi.org/10.1080/02673037.2019.1648772

Basu, S., & Thibodeau, T. (1998). Analysis of Spatial Autocorrelation in House Prices. *Journal of Real Estate Finance and Economics*, *17*(1), 61–85. https://doi.org/10.1023/A:1007703229507

Biswas, A. (2012). Housing submarkets and the impacts of foreclosures on property prices. *Journal of Housing Economics*, *21*(3), 235–245. https://doi.org/10.1016/j.jhe.2012.05.002

Bivand, R. (2017). Creating Neighbours. (Springer-Verlag, Ed.)*The Comprehensive R Archive Network*. New York. https://cran.r-project.org/web/packages/spdep/vignettes/nb.pdf

Bolitzer, B., & Netusil, N. R. (2000). The impact of open spaces on property values in Portland, Oregon. *Journal of Environmental Management*. https://doi.org/10.1006/jema.2000.0351

Bourassa, S. C., Hamelink, F., Hoesli, M., & Macgregor, B. D. (1999). Defining housing submarkets. *Journal of Housing Economics*, *8*(2), 160–183. https://doi.org/10.1006/jhec.1999.0246

Bourassa, S. C., Hoesli, M., & Peng, V. S. (2003). Do housing submarkets really matter? *Journal of Housing Economics*, *12*(1), 12–28. https://doi.org/10.1016/S1051-1377(03)00003-2

Bramley, G., Leishman, C., & Watkins, D. (2008). Understanding neighbourhood housing markets: Regional context, disequilibrium, sub-markets and supply. *Housing Studies*, *23*(2), 179–212. https://doi.org/10.1080/02673030701875113

Chen, W. Y., & Jim, C. Y. (2010). Amenities and disamenities: A hedonic analysis of the heterogeneous urban landscape in Shenzhen (China). *Geographical Journal*, *176*(3), 227–240. https://doi.org/10.1111/j.1475-4959.2010.00358.x

Chen, Z., Cho, S. H., Poudyal, N., & Roberts, R. K. (2009). Forecasting housing prices under different market segmentation assumptions. *Urban Studies*, *46*(1), 167–187. https://doi.org/10.1177/0042098008098641

Chou, J. S., Tserng, H. P., Lin, C., & Huang, W. H. (2015). Strategic governance for modeling institutional framework of public–private partnerships. *Cities*, *42*, 204–211. https://doi.org/10.1016/j.cities.2014.07.003

Choumert, J., Stage, J., & Uwera, C. (2014). Access to water as determinant of rental values: A housing hedonic analysis in Rwanda. *Journal of Housing Economics*, *26*, 48–54. https://doi.org/10.1016/j.jhe.2014.08.001

Competencia, L. (2008). The Anticipated Capitalisation Effect of a New Metro Line on Housing Prices *. *Fiscal Studies*, *29*(2), 233–256

Cox, T., & Hurtubia, R. (2020). Subdividing the sprawl: Endogenous segmentation of housing submarkets in expansion areas of Santiago, Chile. *Environment and Planning B: Urban Analytics and City Science*, *0*(0), 1–17. https://doi.org/10.1177/2399808320947728

Donner, C. (2012). *Housing agents and housing submarkets*. *International Encyclopedia of Housing and Home* (Vol. 3). Elsevier Ltd. https://doi.org/10.1016/B978-0-08-047163-1.00459-8

Fan, Y., Allen, R., & Sun, T. (2014). Spatial mismatch in Beijing, China: Implications of job accessibility for Chinese low-wage workers. *Habitat International*, *44*, 202–210. https://doi.org/10.1016/j.habitatint.2014.06.002

Feng, H., & Lu, M. (2013). School quality and housing prices: Empirical evidence from a natural experiment in Shanghai, China. *Journal of Housing Economics*, *22*(4), 291–307. https://doi.org/10.1016/j.jhe.2013.10.003

Gabriel, S. A., & Wolch, J. R. (1984). Spillover effects of human service facilities in a racially segmented housing market. *Journal of Urban Economics*. https://doi.org/10.1016/0094-1190(84)90031-7

Goodman, A. C. (1981). Housing Submarkets Within Urban Areas: Definitions and Evidence. *Journal of Regional Science*, *21*(2), 175–185. https://doi.org/10.1111/j.1467-9787.1981.tb00693.x

Halket, J., & Pignatti, M. (2015). Homeownership and the scarcity of rentals. *Journal of Monetary Economics*, *76*, 107–123. https://doi.org/10.1016/j.jmoneco.2015.08.003

Haurin, D. R., & Brasington, D. (1996). School Quality and Real House Prices: Inter- and Intrametropolitan Effects. *Journal of Housing Economics*, *5*, 351–368. https://doi.org/10.1006/jhec.1996.0018

Hu, H., Geertman, S., & Hooimeijer, P. (2014). Amenity value in post-industrial Chinese cities: The case of Nanjing. *Urban Geography*, *35*(3), 420–439. https://doi.org/10.1080/02723638.2014.886419

Hu, L., He, S., Han, Z., Xiao, H., Su, S., Weng, M., & Cai, Z. (2019). Monitoring housing rental prices based on social media:An integrated approach of machine-learning algorithms and hedonic modeling to inform equitable housing policies. *Land Use Policy*, *82*(129), 657–673. https://doi.org/10.1016/j.landusepol.2018.12.030

Huang, C., Wang, Y., Li, X., Ren, L., Zhao, J., Hu, Y., et al. (2020). Clinical features of patients infected with 2019 novel coronavirus in Wuhan, China. *The Lancet*, 497–506. https://doi.org/10.1016/s0140-6736(20)30183-5

Huang, Y. (2017). A study of sub-divided units (SDUs) in Hong Kong rental market. *Habitat International*, *62*, 43–50. https://doi.org/10.1016/j.habitatint.2017.02.008

Jang, M., & Kang, C. D. (2015). Retail accessibility and proximity effects on housing prices in Seoul, Korea: A retail type and housing submarket approach. *Habitat International*, *49*, 516–528. https://doi.org/10.1016/j.habitatint.2015.07.004

Jiao, L., & Liu, Y. (2010). Geographic Field Model based hedonic valuation of urban open spaces in Wuhan, China. *Landscape and Urban Planning*, *98*(1), 47–55. https://doi.org/10.1016/j.landurbplan.2010.07.009

Jun, H. J., & Namgung, M. (2018). Determinants of Residential Satisfaction in Housing Submarkets in Seoul. *Journal of Korea Planning Association*, *53*(4), 181–203. https://doi.org/10.17208/jkpa.2018.08.53.4.181

Kang, C. D. (2019). Effects of spatial access to neighborhood land-use density on housing prices: Evidence from a multilevel hedonic analysis in seoul, South Korea. *Environment and Planning B: Urban Analytics and City Science*, *46*(4), 603–625. https://doi.org/10.1177/2399808317721184

Keskin, B., & Watkins, C. (2017). Defining spatial housing submarkets: Exploring the case for expert delineated boundaries. *Urban Studies*, *54*(6), 1446–1462. https://doi.org/10.1177/0042098015620351

Leishman, C. (2009). Spatial change and the structure of urban housing sub-markets. *Housing Studies*, *24*(5), 563–585. https://doi.org/10.1080/02673030903082310

Li, H., Wei, Y. D., & Wu, Y. (2019a). Analyzing the private rental housing market in Shanghai with open data. *Land Use Policy*, *85*(March), 271–284. https://doi.org/10.1016/j.landusepol.2019.04.004

Li, H., Wei, Y. D., Wu, Y., & Tian, G. (2019b). Analyzing housing prices in Shanghai with open data: Amenity, accessibility and urban structure. *Cities*, *91*(November 2018), 165–179. https://doi.org/10.1016/j.cities.2018.11.016

Li, H., Wei, Y. D., Yu, Z., & Tian, G. (2016). Amenity, accessibility and housing values in metropolitan USA: A study of Salt Lake County, Utah. *Cities*, *59*, 113–125. https://doi.org/10.1016/j.cities.2016.07.001

Li, Y., Geertman, S., Hooimeijer, P., Lin, Y., & Yang, H. (2021). Do migrants and locals differ in commuting behavior? A case study of Xiamen, China. *Transport Policy*, *108*(May), 1–10. https://doi.org/10.1016/j.tranpol.2021.04.020

Liang, C. M., Lee, C. C., & Yong, L. R. (2019). Impacts of urban renewal on neighborhood housing prices: predicting response to psychological effects. *Journal of Housing and the Built Environment*, (321). https://doi.org/10.1007/s10901-019-09673-z

Lin, Y., De Meulder, B., Cai, X., Hu, H., & Lai, Y. (2014). Linking social housing provision for rural migrants with the redevelopment of 'villages in the city': A case study of Beijing. *Cities*, *40*, 111–119. https://doi.org/10.1016/j.cities.2014.03.011

Ling, Z., & Hui, E. C. M. (2013). Structural change in housing submarkets in burgeoning real estate market: A case of Hangzhou, China. *Habitat International*, *39*, 214–223. https://doi.org/10.1016/j.habitatint.2012.12.006

Lisi, G. (2019). Property valuation: the hedonic pricing model – location and housing submarkets. *Journal of Property Investment and Finance*, *37*(6), 589–596. https://doi.org/10.1108/JPIF-07-2019-0093

Liu, Y., Tang, S., Geertman, S., Lin, Y., & van Oort, F. (2017). The chain effects of property-led redevelopment in Shenzhen: Price-shadowing and indirect displacement. *Cities*, *67*(June 2016), 31–42. https://doi.org/10.1016/j.cities.2017.04.017

Ma, L. J. C. (2002). Urban transformation in China, 1949–2000: A review and research agenda. *Environment and Planning A*, *34*(9), 1545–1569. https://doi.org/10.1068/a34192

Nilsson, P. (2015). The influence of urban and natural amenities on second home prices. *Journal of Housing and the Built Environment*, *30*(3), 427–450. https://doi.org/10.1007/s10901-014-9421-6

Palm, R. (1978). Spatial Segmentation of the Urban Housing Market. *Economic Geography*. https://doi.org/10.2307/142835

Pride, D., Little, J., & Mueller-Stoffels, M. (2018). The value of residential energy efficiency in interior Alaska: A hedonic pricing analysis. *Energy Policy*, *123*(July 2017), 450–460. https://doi.org/10.1016/j.enpol.2018.09.017

Rosen, S. (1974). Hedonic Prices and Implicit Markets: Product Differentiation in Pure Competition. *Journal of Political Economy*, *82*(1), 34–55

Saleem, H., Jiandong, W., Zaman, K., Elsherbini Elashkar, E., & Mohamd Shoukry, A. (2018). The impact of air-railways transportation, energy demand, bilateral aid flows, and population density on environmental degradation: Evidence from a panel of next-11 countries. *Transportation Research Part D: Transport and Environment*, *62*(February), 152–168. https://doi.org/10.1016/j.trd.2018.02.016

Schnare, A. B., & Struyk, R. J. (1976). Segmentation in urban housing markets. *Journal of Urban Economics*, *3*(2), 146–166. https://doi.org/10.1016/0094-1190(76)90050-4

Song, Y., & Zenou, Y. (2012). Urban villages and housing values in China. *Regional Science and Urban Economics*, *42*(3), 495–505. https://doi.org/10.1016/j.regsciurbeco.2011.06.003

Tian, L. (2006). Impacts of transport projects on residential property values in China: Evidence from two projects in Guangzhou. *Journal of Property Research*, *23*(4), 347–365. https://doi.org/10.1080/09599910601095365

Tse, R. Y. C., & Love, P. E. D. (2000). Measuring residential property values in Hong Kong. *Property Management*, *18*(5), 366–374. https://doi.org/10.1108/02637470010360669

Wang, C. H., & Chen, N. (2020). A geographically weighted regression approach to investigating local built-environment effects on home prices in the housing downturn, recovery, and subsequent increases. *Journal of Housing and the Built Environment*. https://doi.org/10.1007/s10901-020-09742-8

Watkins, C. A. (2001). The definition and identification of housing submarkets. *Environment and Planning A*, *33*(12), 2235–2253. https://doi.org/10.1068/a34162

Wei, Z., Liu, Y., He, S., & Mo, H. (2020). Housing differentiation in transitional urban China. *Cities*, *96*, https://doi.org/10.1016/j.cities.2019.102469. (September 2019

Wen, H., Bu, X., & Qin, Z. (2014). Spatial effect of lake landscape on housing price: A case study of the West Lake in Hangzhou, China. *Habitat International*, *44*, 31–40. https://doi.org/10.1016/j.habitatint.2014.05.001

Wen, H., & Tao, Y. (2015). Polycentric urban structure and housing price in the transitional China: Evidence from Hangzhou. *Habitat International*, *46*, 138–146. https://doi.org/10.1016/j.habitatint.2014.11.006

Wen, H., Zhang, Y., & Zhang, L. (2015). Assessing amenity effects of urban landscapes on housing price in Hangzhou, China. *Urban Forestry and Urban Greening*, *14*(4), 1017–1026. https://doi.org/10.1016/j.ufug.2015.09.013

Wu, C., & Sharma, R. (2012). Housing submarket classification: The role of spatial contiguity. *Applied Geography*, *32*(2), 746–756. https://doi.org/10.1016/j.apgeog.2011.08.011

Xiamen urban planning and design research institute (2015). Xiamen household travel survey in 2015

Xiao, Y. (2017). *Urban Morphology and Housing Market*. Springer Singapore. https://doi.org/10.1007/978-981-10-2762-8

Yang, X., Li, Z., & Webster, C. (2016). Estimating the mediate effect of privately green space on the relationship between urban public green space and property value: Evidence from Shanghai, China. *Land Use Policy*, *54*, 439–447. https://doi.org/10.1016/j.landusepol.2016.03.001

Yuan, F., Wei, Y. D., & Wu, J. (2020). Amenity effects of urban facilities on housing prices in China: Accessibility, scarcity, and urban spaces. *Cities*, *96*(August 2019), 102433. https://doi.org/10.1016/j.cities.2019.102433

Zheng, S., Hu, W., & Wang, R. (2016). How Much Is a Good School Worth in Beijing? Identifying Price Premium with Paired Resale and Rental Data. *Journal of Real Estate Finance and Economics*, *53*(2), 184–199. https://doi.org/10.1007/s11146-015-9513-4