Accessibility to transit, by transit, and property prices: Spatially varying relationships

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Abstract: Accessibility to transit facilities is perceived to affect property prices. However, accessibility by transit has rarely elicited adequate scholarly attention in property price analyses. Additionally, previous studies on how transit accessibility affects property prices mainly focused on rail and bus rapid transit systems, while conventional bus transit, which is very popular in many contexts, has seldom been investigated. Moreover, whether there is spatial heterogeneity in the price (or capitalization) effects of conventional bus accessibility remains to be explored. To fill these gaps, this study aims to investigate the role of accessibility to and by bus in determining housing prices in a bus-dependent city where urban transit service is offered mainly by a bus system rather than other transit systems. Using a database of 4966 condominium units in Xiamen, China, this study develops a battery of spatial econometric models to estimate global and local relationships between to-bus and by-bus accessibility and housing prices. The findings are as below: (1) to-bus accessibility (measured by the number of nearby bus stops) is positively associated with nearby housing prices; (2) by-bus accessibility (measured by travel time to city centers by bus and bus frequency) significantly affects nearby housing prices; (3) spatial heterogeneity exists in the price effects of bus accessibility; and (4) bus frequency exerts a larger price effect in the peripheral area than in the central. Finally, practical and policy implications are discussed.

Keywords: accessibility to transit; accessibility by transit; transit accessibility; spatial heterogeneity; hedonic pricing model; geographically weighted regression; housing price; real estate valuation; urban China

1. Introduction

As an economically feasible and environmentally friendly travel mode, transit (or public transportation) helps reduce automobile usage/dependence and relieve contemporary urban and regional problems (Cervero and Kockelman, 1997; Lu et al., 2018; Zhao et al., 2019). Thus, transit has recently gained considerable attention from both policy makers and academics all over the world. China, which is undergoing rapid urbanization and motorization, is not an exception in this regard (Bao et al., 2019; Hu et al., 2020): numerous transit-promoting approaches (e.g., designation of transit metropolises and implementation/upgrade of modern urban transit (especially metro) systems) and radical automobile-restriction methods (e.g., license plate auction, use restriction based on the last digit of the license plate number, and road space rationing) have been extensively implemented in this country (Lin et al., 2016; Cao, 2017; Jia et al., 2017). Even the United States, which is infamous for its car dependence, is witnessing a resurgence of public transit systems (Schuetz, 2015).

Transit accessibility is often narrowly interpreted as the ease of using the transit service (or "to-transit accessibility"), such as proximity to transit stops (or stations, terminals, depots, berths) and routes. To-transit accessibility is generally depicted by built-environment or "location" variables, such as travel distance/time to transit facilities and the availability of transit services in the neighborhood (Xu et al., 2015, 2018). However, to-transit accessibility is not sufficient for us to enjoy the benefits brought about by transit. Another important condition is the ease of reaching important destinations by the transit system (or "by-transit accessibility") (Dimitriou, 1992; Armstrong and Rodriguez, 2006). By-transit accessibility describes the level of transit service given the ease of accessing such service (Moniruzzaman and Páez, 2012; Pan et al., 2017) and is commonly measured by "service" variables, including headway, travel time/distance, monetary cost, number of transfers, and number of reachable destinations within a predetermined travel time (Xu et al., 2015, 2018; Tribby and Zandbergen, 2012). Therefore, transit accessibility should be interpreted as to-transit and by-transit accessibility combined to acquire an improved understanding of its implications.

Characterized by structural inflexibility, temporal durability, as well as spatial fixity, a house (or residential property) is a commodity with a series of attributes (or characteristics), such as floor area, transit accessibility, and proximity to the city center (So et al., 1997). In a transit-dependent context, to-transit accessibility and by-transit accessibility are likely to be observable utility-bearing characteristics, and they should, in theory, affect housing prices since housing buyers are willing to pay extra for such desirable attributes. While the impact of to-transit accessibility on nearby housing prices has been widely studied in existing literature, the role of by-transit accessibility in shaping property prices remains to be examined thoroughly. As of today, only a few studies have focused on this issue (e.g., Rodríguez and Targa, 2004; Armstrong and Rodriguez, 2006; He, 2020). Moreover, property price determination is a social process, which may vary over space[1]. As such, it is reasonably expected that relationships between transit accessibility and property prices are spatially varying (or heterogeneous, non-stationary). For example, transit accessibility may exert large impacts on property prices in certain locations (e.g., outskirts) and small or imperceptible impacts in other areas (e.g., the central area) (Mulley et al., 2016; Yang et al., 2019).

[1] Unlike stationary physical processes, social processes tend to vary over space, which is termed as "spatial non-stationarity" by Fotheringham et al. (2002). Therefore, the marginal responses of independent variables are expected to be not fixed (but varying) over space. Reasons for this are highly diverse, including sampling variation, intrinsically varying local spatial behavior, model misspecification, and missing variables bias (Fotheringham et al., 2002; Du and Mulley, 2006). Indeed, spatial non-stationarity (or spatial heterogeneity) has been widely observed in a great many previous studies on property price modeling (Fotheringham et al., 2002; Mulley et al., 2016, 2018).

In China, only 36 cities had a metro system as of October 2018, and conventional bus transit is the most popular, if not the only, urban (or intra-city) transit mode in over 300 Chinese cities. In other words, bus-dependent cities, where urban transit service is offered mainly by a conventional bus system rather than other transit systems, account for the majority of Chinese cities (Shen et al., 2018). Therefore, an understanding of the relationship between bus accessibility and nearby housing prices is important for transportation and land use planning for most cities in China and other developing countries. In light of this, based on a dataset of 4966 resale houses in Xiamen (a bus-dependent city as of data collection), we used to-bus and by-bus accessibility to accurately measure the overall bus accessibility of the houses. Following this, we developed both global models (i.e., spatial error model (SEM)) and local models (i.e., geographically weighted regression (GWR) model) to estimate the global and spatially varying effects of bus accessibility on housing prices, respectively.

The contributions of this paper include: (1) extending the two-component transit accessibility modeling approach into the property valuation arena and verifying the role of bus accessibility in shaping property prices in a bus-dependent city of China; (2) providing an empirical analysis on spatially varying relationships between to-bus and by-bus accessibility and housing prices; (3) confirming that bus frequency has a higher price effect in the peripheral area than in the central; and (4) proposing suggestions on value capture schemes and urban development.

The remainder of this paper is organized as follows. Section 2 offers a review of existing literature. Section 3 presents the framework for empirical analysis. Section 4 introduces the data and descriptions of variables. Section 5 discusses the global and local regression results. Section 6 discusses the findings and derives practical and policy implications. Section 7 concludes the paper and summarizes the strengths and limitations of this study.

2. State of the art: transit accessibility and property prices

2.1 To-transit accessibility and property prices

Numerous empirical studies have focused on the effects of to-transit accessibility on property prices. Among transit modes, rail (including high-speed rail, commuter rail, and light/heavy rail) and bus rapid transit (BRT) systems have received much attention in a burgeoning number of studies. The majority of previous property valuation studies have reached a consistent conclusion that to-transit accessibility enhances nearby property prices. There are several meta-analyses and literature reviews on rail and/or BRT systems and property prices, including Debrezion et al. (2007), Mohammad et al. (2013), Stokenberga (2014), Higgins and Kanaroglou (2016), and Ingavardson and Neilsen (2018). They suggested: (1) rail and BRT systems likely enhance nearby property prices, but their price effect estimates considerably vary across previous empirical studies; (2) the price effect is influenced by a host of factors, including but not limited to station-area land use planning, accessibility to stations, the type of transit service and property, demographics, and empirical modeling methods; (3) quintessentially, the rail has a higher effect on nearby property prices than BRT; and (4) the price effects of rail and BRT systems vary across property types (e.g., residential, office, retail, and industrial).

Unlike rail and BRT systems, there is a paucity of research looking at the bus and examining the association between its accessibility and property prices. In stark contrast to the price effects of fixed-guideway transit modes that are relatively consistent, the capitalization effects of the bus are highly elusive: mixed and even conflicting results exist. Most of the research has discovered that the price effects of to-bus accessibility are imperceptible. Cervero and Kang (2011, p. 103) stated that "traditional bus transit services ... fail to confer appreciable accessibility benefits." Empirically, based on hundreds of transactions of single-family properties in Denver between 1969 and 1974, Koutsopoulos (1977) found no appreciable effects of bus accessibility for most routes. So et al. (1997) determined that the price effects of bus accessibility are insignificant in Hong Kong, a city with high metro and bus ridership. Wen et al. (2014, 2017a) indicated the housing price impacts of bus accessibility are insignificant in Hangzhou, China. Moreover, several studies have identified the negative price effects of bus accessibility, which may be attributable to its nuisances (e.g., congestion and noise/air pollution). Cao and Hough (2012) found that bus accessibility negatively influences property rentals in Fargo, the United States, on the basis of hedonic modeling. Wen and Tao (2015) concluded that in Hangzhou, China, bus accessibility is positively and negatively correlated with property prices in 2003 and 2011, respectively. Zhang et al. (2019) reported a negative effect of bus accessibility on housing prices in Hangzhou, China. Furthermore, few studies have determined positive bus accessibility effects on property prices. Zheng and Kahn (2008) concluded that bus accessibility is positively associated with housing prices in Beijing, China. Yang et al. (2019a) developed global regression models to analyze the association between bus accessibility and property prices in Xiamen, China, and their results suggested a positive association. Ibeas et al. (2012) examined the effects of bus accessibility in Santander, Spain, by using a spatial Durbin model, and found that accessibility to bus routes may have a positive price effect. However, the results of Ibeas et al. (ibid) are highly inconsistent: in 8 out of 9 model specifications, the bus price effect is insignificant at the 5% level.

2.2. By-transit accessibility and property prices

Compared with the widely-investigated to-transit accessibility, there is a modicum of research exploring by-transit accessibility and its associations with property prices. Du and Mulley (2006) indicated that by-transit accessibility (measured by transit travel time to secondary school) significantly affects property prices in the Tyne and Wear region (England). In addition, some studies exclusively concentrated on the relationship between by-rail accessibility and housing prices. Chau and Ng (1998) investigated the impact of by-rail accessibility on nearby housing prices in Hong Kong and found that an increase in by-rail accessibility (measured by rail frequency and travel time to CBD) would reduce the price differentials of housing units along the railway line. Armstrong and Rodriguez (2006) appraised the effect of by-rail accessibility (measured by rail travel time to North/South station) on property prices in Eastern Massachusetts, the United States, and claimed that the effect is inconsistent and depends largely on the hedonic functional form. Debrezion et al. (2011) concentrated on the determination process of property prices in three cities of the Netherlands and confirmed that by-rail accessibility (measured by a comprehensive index that incorporates wait time, number of transfers, travel time, and monetary cost) significantly affects property prices in Amsterdam and Enschede, but not in Rotterdam. Li et al. (2019) assessed the price effects of the metro service in Beijing and concluded that by-metro accessibility (measured by metro headway and the number of reachable job opportunities in a predetermined travel time) plays a positive role in the determination of housing prices. Li et al. (2020) confirmed that by-rail accessibility (measured by rail frequency) positively influences housing prices in Melbourne, Australia. Based on property transaction data in 2001 and 2011 in Hong Kong and three-level hierarchical or difference-in-differences (DID) modeling, He (2020) revealed positive associations between by-rail accessibility (measured by a gravity-based variable that considers free-flow travel times to all other locations) and housing prices and found that the positive associations are highly robust across periods and model specifications.

Similarly, quite a few studies focused on the role of by-BRT accessibility in determining housing prices. Rodríguez and Targa (2004) investigated the contributory role of by-BRT accessibility (measured by BRT travel time to the city center) in shaping multi-family housing rentals in Bogotá, Colombia, and suggested that the effect of by-BRT accessibility is statistically significant only when the semi-log functional form is used. Mulley et al. (2014) confirmed that by-BRT accessibility (measured by BRT travel time) positively influences housing prices in Sydney, Australia.

2.3. Spatially varying relationships between transit accessibility and property prices

As noted above, the price effects of transit accessibility are widely examined. Most previous studies, however, adopt global models and do not construct local models to examine local interactions between transit accessibility and housing prices. This global modeling approach hides a huge amount of spatial information on interaction behavior (Fotheringham et al., 2002) and prevents us from gaining a broader picture of how transit accessibility affects property prices.

The local and spatially varying price effects of transit accessibility have been revealed by only a limited number of studies, particularly in the West. Nelson (1992) was among the first to explore whether such effects are spatially stationary or not. The author used separate regression models for low- and high-income areas and found that accessibility to transit has positive and negative price effects on properties in low- and high-income areas, respectively. Yang et al. (2019b) demonstrated that to-BRT accessibility benefits are larger in the peripheral area than in the central area in Xiamen, China. Similarly, He (2020) demonstrated that housing price premiums attributable to by-rail accessibility are more notable in suburban areas than in urban areas in Hong Kong. Higgins (2019) found that the price effects of to-rail accessibility (measured by topography-incorporated walking time) vary across station catchment areas in Hong Kong.

Recently, GWR has been widely utilized to determine the spatially varying capitalization effects of transit accessibility. To the best of our knowledge, the first contribution can be traced to Du and Mulley (2006). Du and Mulley (2006, 2012) reported that the price effects of to-metro and by-transit accessibility vary across space in the Tyne and Wear region (England) and London, respectively. Zhang et al. (2011) confirmed that the association between to-transit accessibility and hotel room prices varies over space in Beijing, China. Mulley (2014) supported the claim that the relationship between BRT accessibility and property prices varies over space in Sydney, Australia. Mulley et al. (2016) demonstrated that the price effects of to-BRT accessibility are larger in the outskirts than in the central area in Brisbane, Australia.

Dziauddin et al. (2014) and Dziauddin (2019) stressed that the relationship between to-rail accessibility and housing prices is spatially varying in Greater Kuala Lumpur, Malaysia. Wen et al. (2017b) identified spatially varying relationships between to-metro accessibility and property prices in Hangzhou, China.

2.4. Thrust of this study

Most previous studies focused on the nexus among rail/BRT accessibility and property prices. However, conventional bus transit, which is the most popular transit mode in urban China, has received much less scholarly attention. In addition, transit accessibility has often been interpreted as accessibility to transit in the property valuation literature, and related studies that simultaneously consider to-transit and by-transit accessibility are vastly limited. Moreover, research on the spatial heterogeneity of the price effects of transit accessibility has mostly been conducted in developed countries (Mulley, 2014; Mulley et al., 2016, 2018). Comparatively, research on the same issue in developing countries, such as China (where bus-dependent cities dominate), is scarce. Thus, more empirical studies on the (spatially varying) price impacts of bus accessibility would shed light on how people value bus accessibility, which has important policy implications for developing countries. This study fills the gaps noted above in several ways. First, it categorizes bus accessibility into two groups and evaluates the role of the two groups of bus accessibility in determining housing prices in a Chinese bus-dependent city. Second, in addition to examining the global relationship between bus accessibility and housing prices, it develops a GWR model to analyze the spatially varying relationships.

3. Methods

3.1. Global regression: hedonic pricing model and SEM

Quintessentially, the hedonic pricing model regresses property prices on a vector of property characteristics, which are often categorized into 3 groups (structure, location, and neighborhood) (Chau and Chin, 2003; Chau et al., 2018; Ko and Cao, 2013; Xiao et al., 2017; He, 2017; Cao and Lou, 2018). Hedonic pricing models assume that the coefficient of each property characteristic does not vary across locations and involve the estimation of global models. However, the use of spatial data (e.g., housing price) cannot meet the underlying assumptions of ordinary least squares (OLS) regression, and thus the traditional hedonic pricing model is often criticized for the shortcoming of inability to deal with spatial autocorrelation (Wong et al., 2013). The hedonic pricing model that incorporates spatial autocorrelation in residuals (i.e., SEM) can be written as follows:

$$Y_i = \alpha + \sum_k X_{ki}\beta_k + \varepsilon_i \,,$$
$$\varepsilon = \lambda W\varepsilon + u$$

where Y_i is the price of property *i*, X_{ki} is the *k*th attribute of property *i*, β_k is the implicit price for attribute *k*, α is a constant, ε_i is a residual that reflects unmeasured variations in property prices and is assumed to be spatially autocorrelated, ε is an n × 1 vector of residuals with its element ε_i, *W* is an n × n weight matrix, λ is the spatial autocorrelation (or autoregressive) parameter, and u is an n × 1 vector of independent residuals. If $\lambda = 0$, the SEM collapses to a traditional hedonic pricing model. α, β_k, and λ are parameters to be jointly estimated.

3.2. Local regression: GWR

Unlike global regression models, GWR models can reflect relationships with a space-varying nature and offer local or location-specific regression results (Xu and Huang, 2015; Yang et al., 2017, 2020; Zhao et al., 2020). Parameter estimates from GWR can be mapped to and visualized over space, which makes the exploration of spatial patterns possible. GWR was initially put forward by Brunsdon et al. (1996) and Fotheringham et al. (2002).

GWR models can be mathematically expressed as follows:

$$Y_i = \alpha(u_i, v_i) + \sum_k X_{ki} \beta_k (u_i, v_i) + \varepsilon_i ,$$

where (u_i, v_i) is the x-y coordinate of point *i*, $\alpha(u_i, v_i)$ is a constant for point *i*, $\beta_k(u_i, v_i)$ is the coefficient of X_{ki}, and all other variables follow previous definitions.

To estimate the local equation of each observation (point), nearby observations need to be weighted, which is commonly conducted by four options, namely fixed Gaussian, fixed bi-square, adaptive Gaussian, and adaptive bi-square kernel functions:

Fixed Gaussian kernel: $w_{ij} = \exp(-d_{ij}{}^2 / \theta^2)$

Adaptive Gaussian kernel: $w_{ij} = \exp(-d_{ij}{}^2 / \theta_{i(k)}{}^2)$

Fixed bi-square kernel: $w_{ij} = \begin{cases} (1 - d_{ij}{}^2 / \theta^2)^2 \text{ if } d_{ij} < \theta \\ 0 \text{ if } d_{ij} \geq \theta \end{cases}$

Adaptive bi-square kernel: $w_{ij} = \begin{cases} (1 - d_{ij}{}^2 / \theta_{i(k)}{}^2)^2 \text{ if } d_{ij} < \theta_{i(k)} \\ 0 \text{ if } d_{ij} \geq \theta_{i(k)} \end{cases}$

where w_{ij} is the weight of point *j* in estimating the local equation of point *i*, d_{ij} is the crow-fly distance between points *i* and *j*, θ is a fixed bandwidth, and $\theta_{i(k)}$ is an adaptive bandwidth defined by the *k*th nearest neighbor distance for estimating the local equation of point *i*.

GWR estimation is computationally intensive because each observation has its own parameter estimates. Typically, in a case with *N* observations and *K* independent variables, the number of regression parameters that need to be estimated is $N \times (K+1)$. The number can be decreased only if one or more parameters are set to be spatially invariant. If all parameters are set to be spatially invariant, a GWR model reduces to the traditional regression model. The sample size in GWR studies is often substantially smaller than that in global modeling studies because of this property of GWR.

4. Data and variables

4.1. Study area and data

Our study area is Xiamen Island, the city proper of Xiamen (Fig. 1). Xiamen (alternatively known as Amoy) is in the southeast part of Fujian Province and at the heart of the Western Taiwan Straits Economic Zone. The permanent population and the land area of Xiamen were 4.11 million and 1700.61 km^2, respectively, in 2018. Commonly known as the “Garden on the Sea” and the “Oriental Hawaii (*dongfang xiaweiyi*)”, Xiamen is a glamorous international seaport city and a famous and cozy tourist destination with stunning landscapes and has an eye-catching, picturesque UNESCO World Heritage Site (i.e., Kulangsu, also named as Gulangyu). The gross domestic product (GDP) of Xiamen in 2018 was 479.1 billion yuan according to the Xiamen Statistical Yearbook. Similar to most Chinese cities, Xiamen has high transit ridership. During the observation period, Xiamen had not developed its metro system[2]. In this sense, the city is a good representation of many cities in China.

[2] A metro system was open on 31st December 2017, circa nine months after the data collection period.

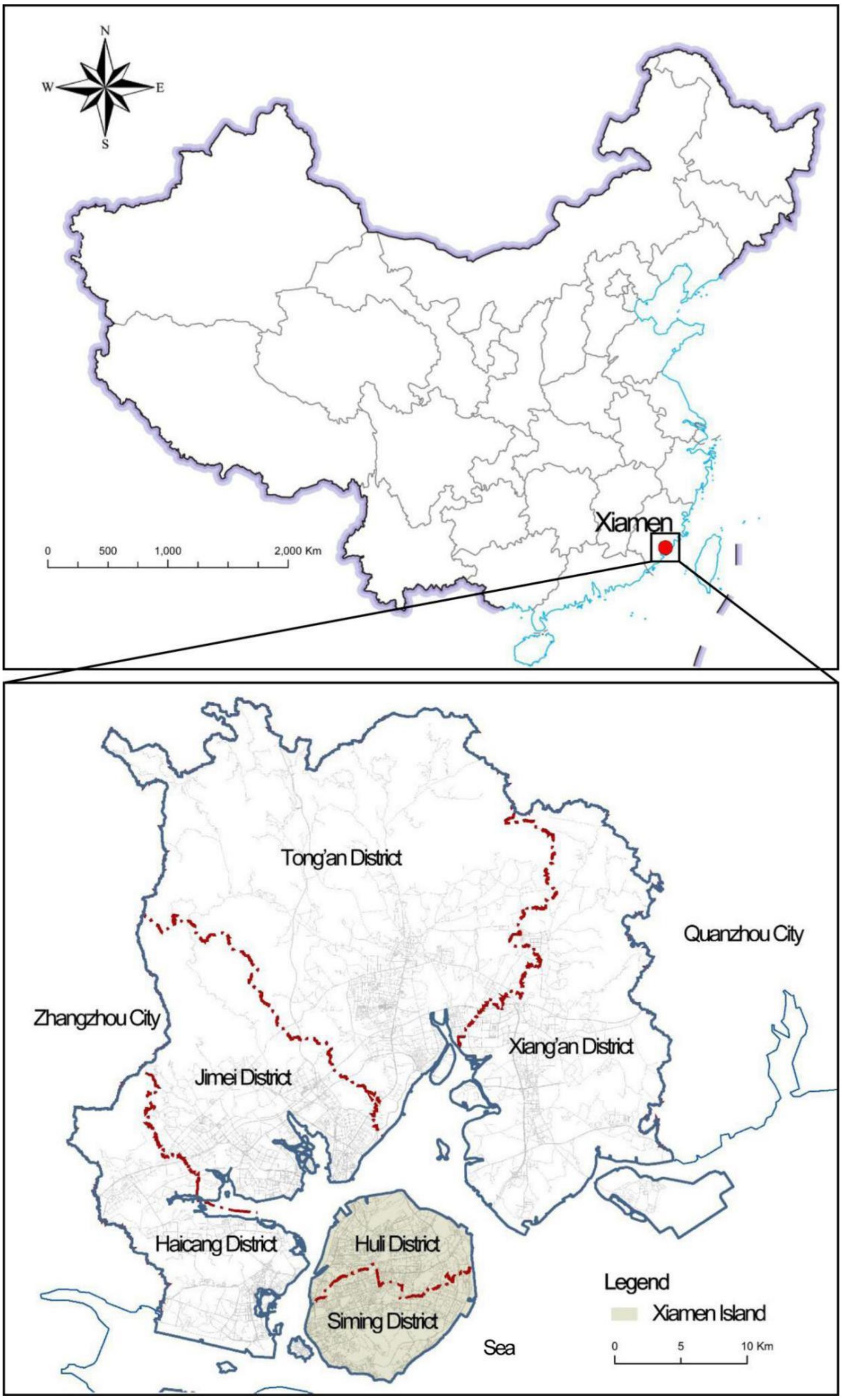

Fig. 1. Location of Xiamen City and Xiamen Island
Source: Made by the authors

Xiamen Island, located in the south of the city, is the political, economic, and financial center of Xiamen. It has an area of around 130 km^2 and a permanent population of over 2 million. Located in the southwest of the island, from which the city originates, Zhongshan Road (Fig. 2) is normally regarded as the old or traditional city center (Yang et al., 2019a, 2019b), while Wuyuan Bay, situated in the northeast, is a new city center (Fig. 2). Siming District (southern part) is the central area of the island, while Huli District (northern part) is the peripheral area (see Fig. 1). A compelling reason for the selection of the study area is that the scale and clear spatial boundary of the area reduce modeling complexity and ameliorate, albeit do not completely resolve, the missing variable bias (a recognized and much-derided problem of hedonic modeling).

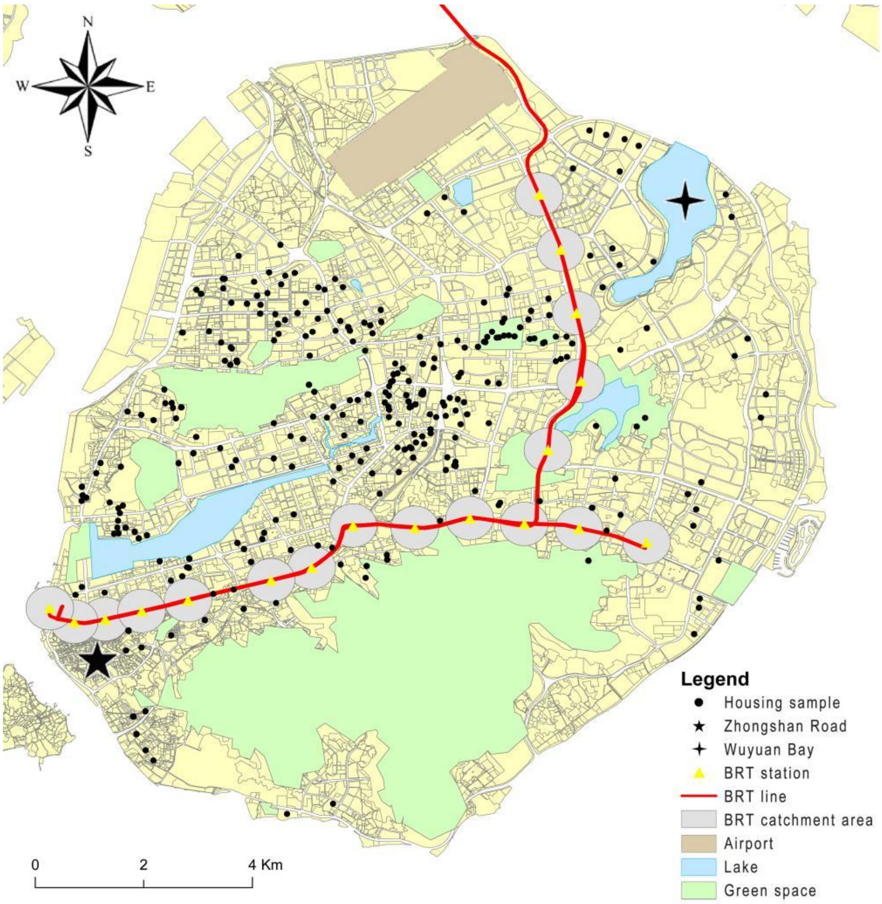

Fig. 2. Map of the study area
Source: Made by the authors

The BRT system of Xiamen Island operates in the elevated and dedicated right-of-way (Fig. 3). Comparatively, the conventional bus runs on the street network in mixed traffic, and its system was firstly operated in 1957 in Xiamen and became popular during the 1990s. The bus accounted for 31.7% of trips made by residents in Xiamen Island, while the BRT and the car only constituted 6.9% and 9.3%, respectively (Zhou et al., 2011).

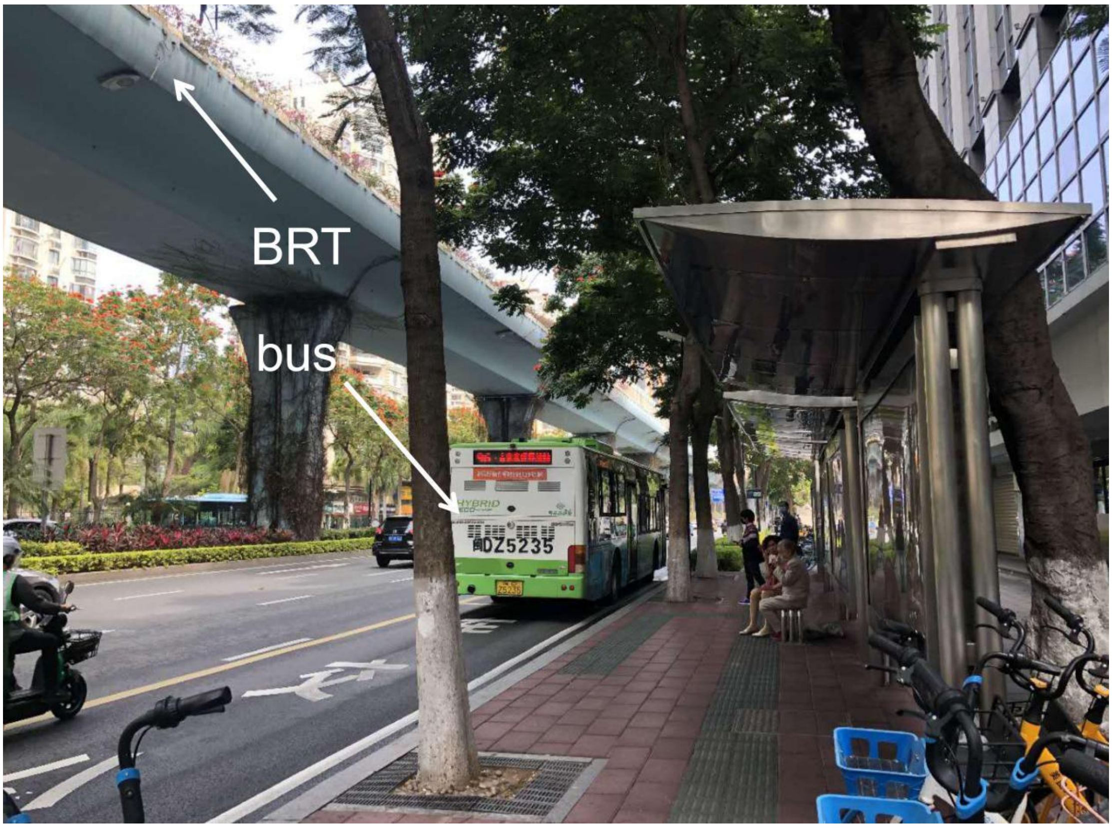

Fig. 3 Comparison of BRT and the bus

The condominium unit (residing in the gated community or residential district) is the main housing type in urban China with a market share of more than 95% (Wu et al., 2014). Normally, in urban China, a gated community is developed by a single developer and consists of hundreds and even thousands of condominium units. Given this feature, this study only considered condominium units. A dataset of 5647 resale condominium units was crawled from a popular housing agency website, *Fang.com*, in late March 2017. To effectively remove the price effects of BRT accessibility and single out those of bus accessibility, observations within a 400-meter radius from the BRT system (i.e., BRT catchment area, shown in the grey background in Fig. 2) were excluded, and a total of 4966 house observations were left for subsequent analysis.

The information on the asking (or listing) price, structural variables, and the name and location (longitude and latitude) of the community of the units was directly obtained from the website. Then, according to the location information, the units were geo-coded into a GIS system to facilitate the measurement of neighborhood and locational variables used for hedonic modeling. The neighborhood was set as the traffic analysis zone delineated by the Xiamen Transport Bureau. The units were geographically spread throughout the study area, except for the northwest area dominated by industrial land and areas adjacent to eastern and southern coasts, where property development is strictly forbidden by the city government (Fig. 2).

4.2. Description of variables

Table 1 lists the definitions and expected signs of coefficients of variables. Guided by the framework of hedonic modeling, this study selected 16 control variables (including 5 structural, 5 locational, and 6 neighborhood variables)[3] and 4 explanatory variables. The number of bedrooms was measured with a set of dichotomous variables, following Malpezzi (2003). Compared with using a discrete integer variable (= 1, 2, 3, ...), this approach has higher flexibility and more importantly can avoid the multi-collinearity problem, given that the number of bedrooms and the gross floor area are highly correlated.

Table 1 Definitions and expected signs of the coefficients of variables (N=4966)

Variable	Variable definition	Expected sign
Dependent variable		
Price	Price of the property (10^4 yuan)	/
Control variable		
Size	Gross floor area (m^2)	+
Age	Age of the property (year)	-
Building height	Number of stories	+
Bedroom2-	Dichotomous variable that equals 1 if the property has 1 or 2 bedrooms and 0 otherwise	/
Bedroom3	Dichotomous variable that equals 1 if the property has 3 bedrooms and 0 otherwise	+
Bedroom4+	Dichotomous variable that equals 1 if the property has 4 or more bedrooms and 0 otherwise	+
Distance to the old city center	Distance between the property and Zhongshan Road (km)	-
Distance to the new city center	Distance between the property and Wuyuan Bay (km)	-
Distance to the sea	Distance between the property and the sea (km)	-
Distance to the airport	Distance between the property and Xiamen Gaoqi International Airport (km)	+
Distance to the shopping center	Distance between the property and the closest shopping center (km)	-
Community environment	Dichotomous variable that equals 1 if the property is located in a community with a good environment and 0 otherwise	+
Population density	Neighborhood-level population density (10^3/km^2)	-
Employment density	Neighborhood-level job density (10^3/km^2)	+
School quality	Dichotomous variable that equals 1 if the property is within the attendance zone of a prestigious (province-level demonstration) elementary school and 0 otherwise	+
Elevated roads	Dichotomous variable that equals 1 if the property is within 500 m of elevated roads and 0 otherwise	-

[3] Bedroom2- is excluded from the regression models to avoid the multi-collinearity problem.

Waterbody	Dichotomous variable that equals 1 if the property is within 200 m of a waterbody and 0 otherwise	+
Explanatory variable (to-bus accessibility variable)		
Number of bus stops	Number of bus stops within 500 m	+
Explanatory variable (by-bus accessibility variable)		
Travel time to the old city center	Travel time to Zhongshan Road by bus (min)	-
Travel time to the new city center	Travel time to Wuyuan Bay by bus (min)	-
Bus frequency	Neighborhood-level bus frequency (departures/hour)	+

The measurement of bus accessibility is of paramount importance to this study. To-bus accessibility was assessed by the "cumulative opportunity" approach instead of the "nearest opportunity" for the following reason. Like other Chinese cities, the study area is dominated by large-scale gated communities (Wu et al., 2014). Normally, a gated community has many entrances, through which residents can access diversified bus stops. Residents do not always access the closest stop but choose a nearby stop with desirable routes and schedules. To-bus accessibility was initially measured with two variables, namely, the number of bus stops and that of bus routes within 500 m. However, due to the high correlation between the two, the number of bus routes was excluded in the subsequent hedonic analysis to avoid the multi-collinearity problem[4].

By-bus accessibility was measured using three variables, namely, bus travel time to two city centers and bus frequency. The contributory role of bus frequency in shaping property prices has rarely been investigated (Li et al., 2020). We assume that bus frequency matters in shaping property prices because this variable directly determines wait time (how quickly riders can get service), which is what users would like to minimize, especially in an outdoor environment with air pollutants from cars. Furthermore, for riders, wait time is often considered to be more unpleasant than in-vehicle time and longer than what it actually is (Truong and Hensher, 1985; Wardman, 2004).

Table 2 presents descriptive statistics of variables. The property price ranges from 0.8 to 50 million yuan, with an average of 7.59 million yuan. (1 yuan is equivalent to 0.142 US dollar.)

Table 2 Descriptive statistics of variables

Variable	Minimum	Maximum	Mean	Standard Deviation

[4] We replaced the number of bus stops with the number of bus routes and repeated the hedonic analysis. The performance of the two to-bus accessibility measures was highly similar.

Price (10^4 yuan)	80	5000	758.56	463.76
Size (m^2)	26	400	134.95	63.21
Age (year)	1	28	10.47	6.07
Building height	1	44	19.19	10.99
Bedroom2-	0	1	0.24	0.43
Bedroom3	0	1	0.41	0.49
Bedroom4+	0	1	0.36	0.48
Distance to the old city center (km)	0.37	13.43	7.84	2.96
Distance to the new city center (km)	0.09	11.07	4.13	2.57
Distance to the sea (km)	0.14	6.18	3.13	1.67
Distance to the airport (km)	1.00	11.18	5.27	1.82
Distance to the shopping center (km)	0.37	6.28	2.26	1.34
Community environment	0	1	0.65	0.48
Population density ($10^3/km^2$)	2.07	37.39	15.91	9.49
Employment density ($10^3/km^2$)	0.19	70.24	16.28	17.39
School quality	0	1	0.12	0.32
Elevated roads	0	1	0.11	0.31
Waterbody	0	1	0.11	0.31
To-bus accessibility variable				
Number of bus stops	0	21	6.02	4.05
By-bus accessibility variable				
Travel time to the old city center (min)	3	90	52.34	14.72
Travel time to the new city center (min)	3	73	26.28	11.24
Bus frequency (departures/hour)	5.78	9.00	7.83	0.75

5. Modeling results

A pairwise correlation analysis was performed to examine the correlations among regressors, and the results showed that no multi-collinearity exists in this study. Moreover, *Geoda (v 1.14)* and *GWR (v 4.0)* were used to estimate global and local models, respectively.

5.1. Global regression

Linear, semi-log (log-linear), and double-log functional forms were initially estimated to determine the best model specification. The results indicate that the double-log functional form fits the data best. Seven regressors (i.e., Bedroom3, Bedroom4+, Community environment, School quality, Elevated roads, Waterbody, and Number of bus stops) were not transformed into a natural logarithmic form on account of the non-positive definiteness.

To detect the presence of spatial autocorrelation in the data, a Moran's *I* test was performed, and the results (Moran's *I* value = 0.610, $p < 0.01$) illustrate that the spatial autocorrelation is significant (Fig. 3). As such, spatial econometric models rather than OLS regression models should be employed.

To better illustrate the explanatory power of bus accessibility variables in shaping housing prices, four SEMs were developed, and their regressors include only control variables (Model 1), control variables + to-bus variable (Model 2), control variables + by-bus variables (Model 3), and all independent variables (Model 4), respectively. Table 3 shows the outcomes of the four SEMs. The models perform reasonably well, exhibiting high goodness of fit. They explain approximately 91% of the variation of the explained variable (i.e., housing price) and leave only around 9% of the variation of housing prices unexplained. We can also see the gradual increment in the goodness of fit with the introduction of the bus accessibility variable(s). More importantly, all the bus accessibility variables are significant at the 1% level in all the four models.

Table 3
Parameter summary of the global regression models

Variable	Model 1 Coefficient (*z*-value)	Model 2 Coefficient (*z*-value)	Model 3 Coefficient (*z*-value)	Model 4 Coefficient (*z*-value)	Model 5 Coefficient (*z*-value)
Size	0.877** (88.75)	0.877** (88.83)	0.884** (89.02)	0.884** (89.01)	0.887** (89.41)
Age	-0.103** (-18.08)	-0.101** (-17.80)	-0.128** (-23.17)	-0.128** (-23.15)	-0.100** (-17.65)
Building height	0.072** (12.28)	0.072** (12.26)	0.065** (11.19)	0.065** (11.17)	0.071** (12.16)
Bedroom3	0.084** (9.92)	0.083** (9.79)	0.078** (9.21)	0.077** (9.14)	0.079** (9.31)
Bedroom4+	0.149** (12.80)	0.149** (12.85)	0.139** (12.02)	0.140** (12.06)	0.141** (12.13)
Distance to the old city center	-0.097** (-8.94)	-0.099** (-9.11)	/	/	-0.096** (-8.92)
Distance to the new city center	-0.037** (-7.06)	-0.039** (-7.48)	/	/	-0.036** (-6.99)
Distance to the sea	-0.099** (-17.52)	-0.097** (-16.90)	-0.124** (-24.11)	-0.123** (-23.81)	-0.097** (-16.99)
Distance to the airport	-0.034** (-2.82)	-0.034** (-2.86)	0.010 (0.91)	0.008 (0.73)	-0.005 (-0.36)
Distance to the shopping center	-0.194** (-25.83)	-0.196** (-26.09)	-0.166** (-21.22)	-0.169** (-21.42)	-0.177** (-22.21)
Community environment	0.075** (9.88)	0.100** (9.67)	0.080** (10.65)	0.100** (9.77)	0.102** (9.87)
Population density	-0.074** (-9.85)	-0.076** (-10.12)	-0.049** (-7.09)	-0.050** (-7.32)	-0.073** (-9.73)
Employment density	0.049** (14.76)	0.046** (13.44)	0.044** (12.81)	0.042** (11.94)	0.039** (11.17)

School quality	0.080** (8.46)	0.079** (8.33)	0.091** (9.69)	0.090** (9.57)	0.085** (9.02)
Elevated roads	-0.142** (-11.02)	-0.156** (-11.59)	-0.117** (-9.04)	-0.128** (-9.48)	-0.145** (-10.76)
Waterbody	-0.021* (-2.07)	-0.019 (-1.83)	0.020* (2.11)	0.023* (2.45)	-0.012 (-1.16)
<u>To-bus accessibility variable</u>					
Number of bus stops	/	0.005** (3.56)	/	0.004** (2.83)	0.004** (3.17)
<u>By-bus accessibility variable</u>					
Travel time to the old city center	/	/	-0.081** (-6.39)	-0.080** (-6.29)	/
Travel time to the new city center	/	/	-0.056** (-9.01)	-0.057** (-9.21)	/
Bus frequency	/	/	0.258** (7.43)	0.254** (7.32)	0.256** (7.37)
Constant	2.993** (44.00)	2.969** (43.47)	2.498** (20.47)	2.484** (20.37)	2.325** 21.03
λ	0.222** (5.12)	0.222** (5.15)	0.200** (4.55)	0.199** (4.53)	0.218** (5.02)
Performance statistics					
R^2	0.9077	0.9079	0.9090	0.9091	0.9089
AIC	-2446.65	-2457.30	-2518.01	-2524.01	-2509.33
Log-likelihood	1240.32	1246.65	1277.01	1281.00	1273.66

Note: ** Significant at the 1% level, * Significant at the 5% level.

The current modeling results are in line with previous hedonic studies. First, size is the most significant independent variable (with the largest *z*-value), which is highly logical. Second, age has negative impacts on property prices, indicating that housing buyers prefer newer properties with less physical deterioration over time. Third, building height is positively related to housing prices, implying that residents are inclined to live in high-rise buildings. This agrees with reality and concurs with existing literature (Yang et al., 2019b). Fourth, adjacency to elevated roads negatively affects the prices. Last, two control variables, namely Distance to the airport and Waterbody, perform inconsistently across the four models. In the full model (Model 4), the former is insignificant, while the latter has a significant positive coefficient. This observation indicates that distance to the airport does not significantly determine housing prices, whereas proximity to a waterbody positively affects the prices.

The interpretation of the performance of the four bus accessibility variables is of primary interest. Notably, all explanatory variables are significant at the 99% confidence level. The to-bus accessibility variable, Number of bus stops, has a coefficient of 0.004. This finding implies that an additional bus stop within 500 meters of the community would induce a 0.4% increase in housing prices and supports the claim that conventional bus transit provides perceivable accessibility benefits. This result disagrees with those obtained in car-dominant (Koutsopoulos, 1977; Cao and Hough, 2008) or metro-served cities (So et al., 1997; Wen et al., 2017b; Zhang et al., 2019). Meanwhile, the three by-bus accessibility variables are significant at the 99% confidence level, and the associated coefficients have expected signs. Bus travel time to the traditional or new city center has negative impacts on property prices, indicating that housing buyers are willing to pay for shorter by-bus travel time. Furthermore, bus frequency has positive impacts on property prices, suggesting that property buyers are willing to pay to shorten the potential bus wait time.

Obviously, bus travel time is highly correlated with distance. Therefore, one may argue that the two bus travel time variables only reflect the accessibility to city centers rather than by-bus accessibility to the centers. In light of this, we replaced the two travel time variables in Model 4 with two distance variables and developed Model 5. The results are shown in the last column of Table 3. Observe that Model 5 is slightly outperformed by Model 4, and bus frequency is still significant at the 5% level. This result offers some evidence supporting the significant role of by-bus accessibility in shaping housing prices in the study area.

In summary, the performance of the to-bus and by-bus accessibility variables meets our expectations. The global regression results indicate that houses with good to-bus and/or by-bus accessibility have higher prices and confirm that the two components of bus accessibility are crucial in shaping housing prices.

5.2. Local regression

Table 4 shows the GWR modeling result (with an adaptive Gaussian kernel function), illustrating that the GWR model outperforms the global model (Model 4) as suggested by its higher R^2 (0.9392 as compared to 0.9091), lower AIC (-4395.90 as compared to -2524.01), and higher log-likelihood (2281.78 as compared to 1281.00). This result indicates the presence of spatial heterogeneity in the housing market of Xiamen Island. Moreover, a substantial discrepancy is observed between global and local estimates, and the majority of the variables (except for Size, Bedroom3, Bedroom4+, and Elevated roads) have divergent influencing directions. However, the improvement of the model fit is not without sacrifice. We examined the residuals from the GWR model and the SEM and found that the Moran' *I* value is higher in the GWR model. This illustrates that spatial autocorrelation exists in residuals of the GWR model, but not those of the SEM.

Table 4
Parameter summary of GWR model estimates and ANOVA table

Variable	Min	Lower quartile	Median	Upper quartile	Max
Size	0.796	0.839	0.876	0.902	0.980
Age	-0.240	-0.180	-0.130	-0.078	0.001
Building height	-0.038	0.020	0.043	0.058	0.117
Bedroom3	0.022	0.053	0.066	0.077	0.109
Bedroom4+	0.061	0.091	0.109	0.122	0.165
Distance to the sea	-0.460	-0.130	-0.042	0.033	0.490
Distance to the airport	-0.263	-0.033	0.100	0.226	0.539
Distance to the shopping center	-0.307	-0.154	-0.097	-0.054	0.492
Community environment	-0.307	0.039	0.096	0.135	0.348
Population density	-0.298	-0.071	-0.069	-0.036	0.297
Employment density	-0.031	-0.009	0.028	0.070	0.110
School quality	-0.610	-0.003	0.001	0.071	0.344
Elevated roads	-0.376	-0.210	-0.168	-0.114	-0.009
Waterbody	-0.133	0.000	0.066	0.064	0.556
<u>To-bus accessibility variable</u>					
Number of bus stops	-0.045	-0.003	0.007	0.021	0.034
<u>By-bus accessibility variable</u>					
Travel time to the old city center	-0.386	-0.075	-0.002	0.066	0.250
Travel time to the new city center	-0.189	-0.078	-0.017	0.046	0.137
Bus frequency	-0.667	-0.374	0.137	0.454	2.676
Constant	-1.724	1.352	2.135	2.931	4.225
Performance statistics					
R^2	0.9392				
AIC	-4395.90				
Log-likelihood	2281.78				
ANOVA	Sum of residuals	df	*F*-value		
Global residuals	174.172	4947	-		
GWR improvement	58.179	86.478	-		
GWR residuals	115.993	4860.522	28.191		

The interpretation of the performance of the four bus accessibility variables is the primary interest of this study. Table 4 implies that the coefficient of each bus accessibility variable significantly varies across locations. This result suggests that the global model, while useful in showing the average direction and magnitude of influence of the four bus accessibility variables, is inadequate in estimating the spatially varying impacts of these variables. This finding supports the argument of Mulley (2014) that using a single, average, and global value for policy making is inappropriate.

For the improved visual inspection and examination of the local parameter estimates (or coefficients), Figs. 4-7 map the coefficients of the four variables of key interest via inverse distance weighted (IDW) interpolation in *ArcGIS 10*, respectively. Spatial heterogeneity exists in the capitalization effects of bus accessibility, and positive relationships between bus accessibility and housing prices can be observed in most places. This result is in line with that of the global model. Fig. 4 reveals that to-bus accessibility premiums can be identified in a large portion of the island, and they seem higher around the geometric center of this island than in other areas.

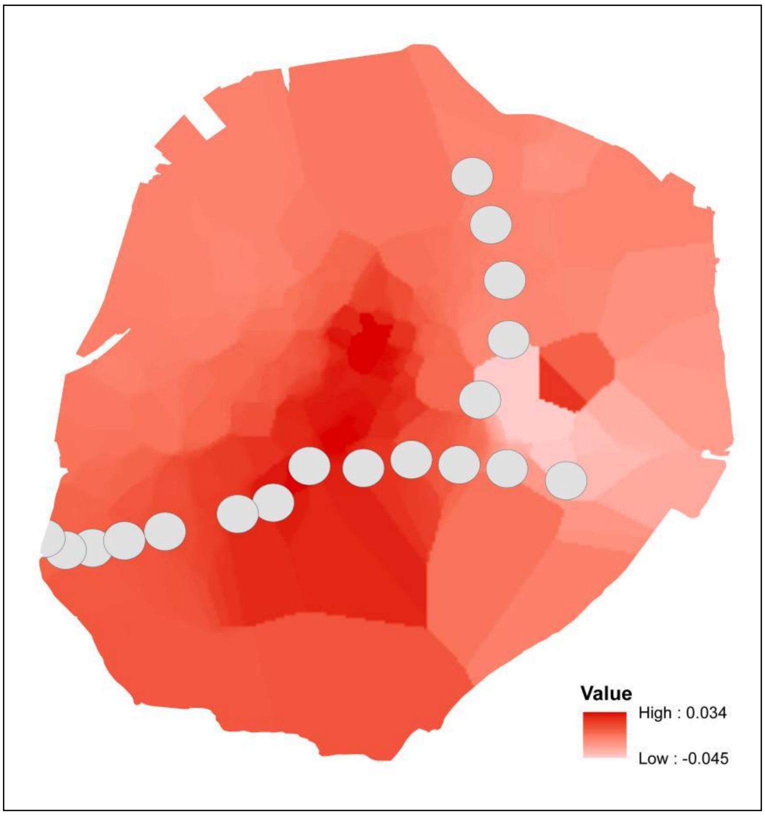

Fig. 4. Map of the local coefficients of Number of bus stops

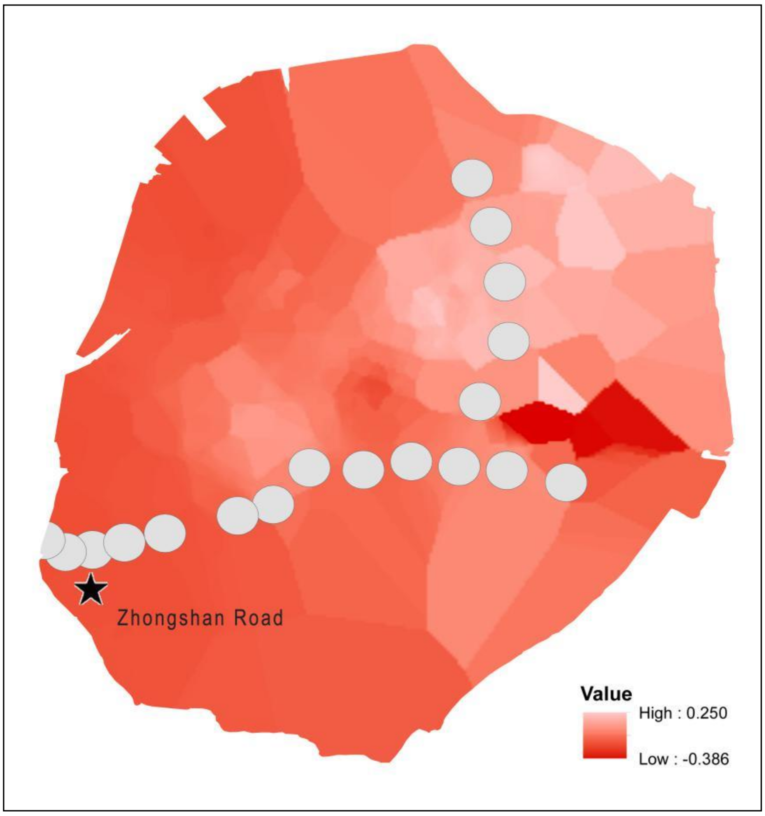

Fig. 5. Map of the local coefficients of Travel time to the old city center

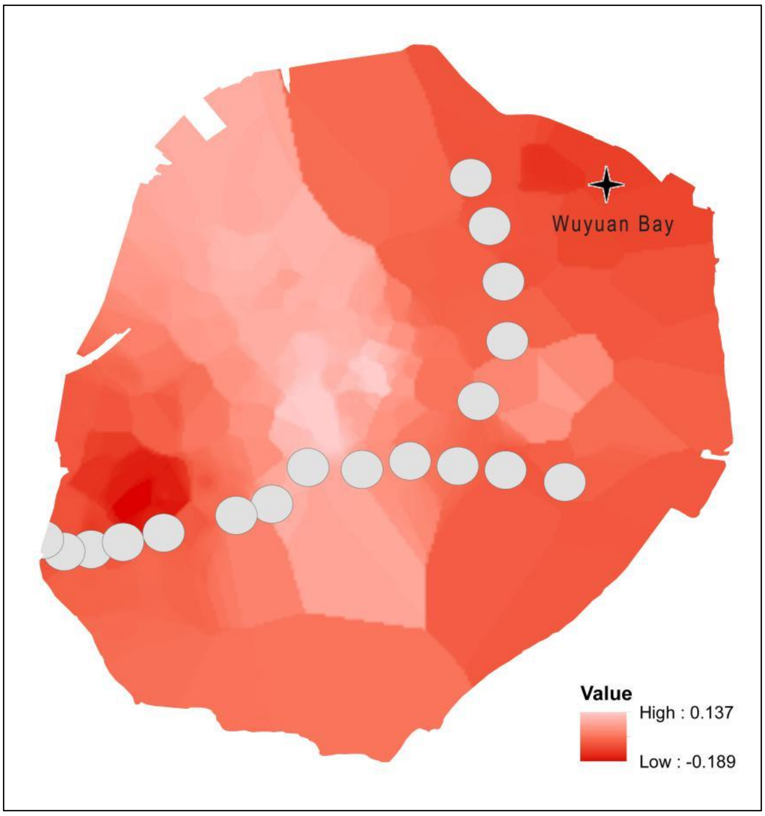

Fig. 6. Map of the local coefficients of Travel time to the new city center

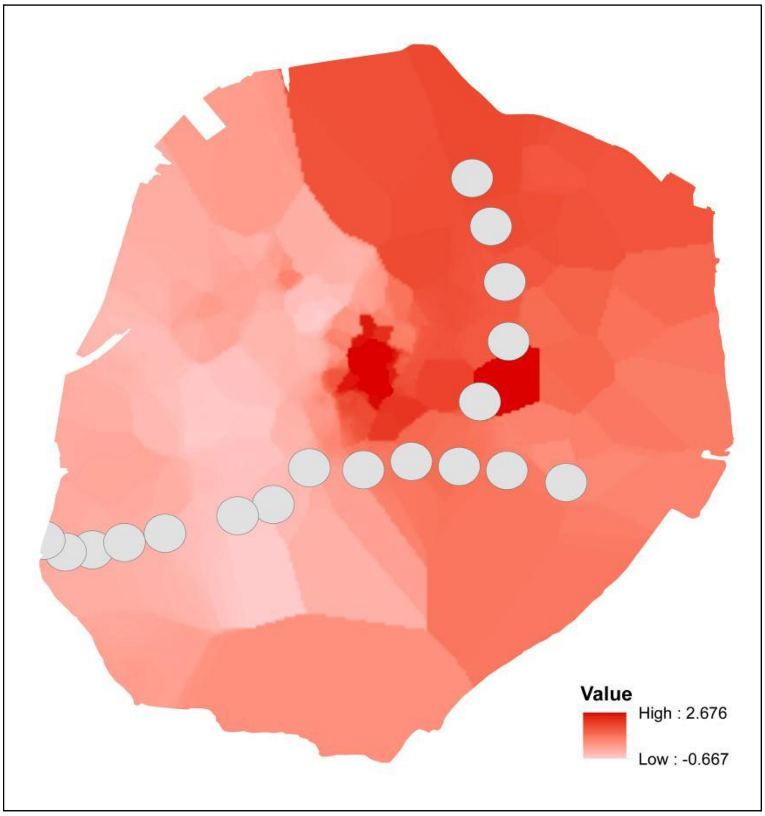

Fig. 7. Map of the local coefficients of Bus frequency

Interestingly, Fig. 7 indicates that bus frequency has a larger positive price effect in the peripheral area (northern part) than in the central (southern part). This outcome implies that an increase in bus frequency has lower positive impacts on property prices in the central city area where more travel options are available, which is consistent with the law of diminishing marginal returns. Put in another way, the enhancement of the transit service by increasing transit frequency should, in theory, have larger positive impacts on property prices in the peripheral area where fewer alternative transit options are available. This can be observed in our GWR results.

6. Discussion

Previous studies, mostly conducted in car-dominant or metro-served settings, generally agree that to-bus accessibility exerts an imperceptible effect on housing prices. On the one hand, in car-dominant contexts where conventional bus transit plays an insignificant role for residents, the insignificant price effects of bus accessibility are logical. On the other hand, in metro-served contexts, the metro is always the back-bone of the urban transport system, and buses have a subsidiary or supplementary function. Therefore, positive, negligible, or even negative price effects of bus accessibility are possible in the two contexts. We argue that such outcomes, however, cannot be generalized to bus-dependent cities where bus transit is crucial in people's daily life (Yang et al., 2019a). In this study, we identified significant (but spatially varying) price premiums stemming from bus accessibility in a bus-dependent city based on hedonic modeling. An explanation is that the high quality of bus services makes to-bus accessibility valuable or desirable and also makes Xiamen a bus-dependent city (as of the data collection period).

The study has profound practical implications. It provides guidance to the planning and design of cities with an adequate level of transit accessibility. In addition, this study provides strong evidence on value creation and offers a basis for establishing evidence-based approaches to implement value capture schemes for (co-)financing transit investments. At present, as an administratively simple approach, tax-based value capture schemes have pervasively applied in numerous cities or countries. However, as yet, in Mainland China, only Shanghai and Chongqing levy property tax, and the absence of property tax is an inherent institutional barrier of a sea of Mainland Chinese cities to (co-)financing transit investments. As such, residents of China always benefit from transit investments without any cost; and the current approach of relying only on land leasing revenues and bank debts is not conducive to the sustainable development of transit services. In China, owing to the difficulty or infeasibility of tax-based value capture schemes, governments need to explore other approaches to capture the added value provided by transit investments. Numerous municipal governments are now exploring various value capture schemes, but nearly all of them still fail to find an effective and efficient one. A handful of Mainland Chinese cities (e.g., Beijing, Shenzhen, and Wuhan) use several innovative strategies, including but not limited to rail plus property, two-step bidding, and land reserve (Wang et al., 2019). In the years to come, most cities can test such China-specific strategies and explore novel methods, such as predetermined land reserve (Sun et al., 2017).

Given the spatially varying capitalization effects of transit accessibility that we identified, the disregard of spatial heterogeneity would result in misleading and even erroneous policy prescriptions. That is, a universal value capture scheme is certainly inappropriate and eventually leads to spatial inequity. Devising spatially varying value capture schemes is therefore indispensable. But it should be noted that conventional bus transit systems are different from fixed-way transit systems in the following two aspects: (1) Normally, they do not require large amounts of investment on fixed infrastructure. (2) It is much easier to change routes of a bus system than rails or BRTs, which means that the price effects of buses on properties might not be as consistent as rails/BRTs. Subsequently, it is difficult to capture the values of the external effects of a bus system.

Our findings can provide some useful implications for property developers and investors to make informed choices and reduce risks when they make an investment. For example, it is favorable for property developers to rent the land and construct condominiums around the areas where governments will potentially provide good bus services since such condominium units have high demands and are likely to sell well. Moreover, we find that bus frequency exerts a larger price effect in the peripheral area than in the central. This indicates that in a bus-dependent city, residents in the peripheral area desire high bus accessibility. Therefore, to reduce social inequality, it is both urgent and necessary for governments to improve the bus accessibility (more broadly, bus service) in the peripheral or suburban area, where many low-incomers dwell. Consequently, these disadvantageous people could have higher mobility levels and lower commuting costs.

7. Conclusions

This study argues that by-transit accessibility is a factor in need of examination in property price modeling and elaborates on the role of bus accessibility in shaping housing prices in a bus-dependent city. Using a database of 4966 condominium units in Xiamen Island, we simultaneously considered accessibility to bus and by bus and developed a swathe of spatial econometric models to examine the relationships between bus accessibility and housing prices. The empirical findings are summarized below: 1) accessibility to bus positively influences nearby property prices; 2) accessibility by bus, measured by bus travel time to city centers and bus frequency, have significant effects on nearby property prices; 3) the impacts of bus accessibility on nearby housing prices exhibited spatial heterogeneity; and 4) bus frequency exerts a larger price effect in the peripheral area than in the central area.

This study has many strengths. (1) It applies the two-component transit accessibility approach in a property valuation study in urban China, where limited scholarly attention has been poured into. (2) It focuses on the conventional bus system, which has seldom elicited scholarly attention. (3) It offers empirical evidence on the spatially varying relationships between to-bus and by-bus accessibility and property prices and reveals quite a few interesting findings (e.g., higher price effects of bus frequency in the peripheral area).

However, this study is not wholly beyond reproach, and it indeed has some weaknesses. (1) Due to data unavailability, we only focus on four bus accessibility variables in this study and do not investigate other relevant variables (e.g., availability and quality of sidewalk to bus stops and the number of transfers/interchanges in reaching city centers). (2) Restricted by data availability, the property prices utilized for empirical analysis are asking (or listing) prices that represent how sellers value the property instead of transaction prices that truly reflect how the market (sellers and buyers) values the property. It is recognized that the transaction price is a better indicator (than the asking price) in property valuation studies. However, we feel that our approach is acceptable for the following reasons: asking and transaction prices are often highly correlated (Salon et al., 2014; Ibeas et al., 2012); during the data collection period (March 2017), Xiamen's housing market was a seller's market, in which sellers have strong pricing power and buyers have limited negotiating/bargaining space. Therefore, asking prices listed in *Fang.com* were very close to transaction prices, which has been validated by Salon et al.'s (2014) discussions with local real estate professionals; and unless the price differential is systematically related to one of the other variables, using the asking price data would not considerably distort parameter estimates (Kim, 2016). (3) Our motivation for using global spatial econometric methods rather than the OLS model is addressing spatial autocorrelation in the spatial data. We compared the performance of the SEM and the SLM (another basic spatial autocorrelation model) and found that the SEM outperforms the SLM in modeling our data, although the difference in modeling results is rather small. We, therefore, opt for the SEM, which is acceptable because the concern of this study is "correcting the potentially biasing influence of spatial autocorrelation, due to the use of spatial data" rather than "the assessment of the existence and strength of spatial interaction" (Anselin, 2001, p. 316). However, many non-basic spatial econometric models, such as the spatial Durbin model, the Kelejian-Prucha model, the spatially lagged X model, and the Manski model, can be tested in upcoming research. (4) The anticipation effects of transit may exist in the housing market. However, Yang et al. (2019b) developed hedonic pricing models to test the presence of anticipation effects of the metro in Xiamen Island, and their results suggested that the anticipation effects on housing prices are insignificant in the study area. The reason provided by the authors is that positive price anticipation effects are counterbalanced by nuisances attributed to large-scale excavation projects for metro construction This study, therefore, follows the authors' argument and does not devise sophisticated modeling approaches, predominately due to data unavailability. Notwithstanding, we agree that the anticipated effects of the metro should be thoroughly investigated by rigorous research design (e.g., DID modeling, regression discontinuity design, propensity score matching, and coarsen exact matching) with longitudinal property transaction data.

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