An Evaluation of the Capitalization Effect of Walking Accessibility in Xiamen, China

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ABSTRACT

Walking is an imperative and eco-friendly travel mode. Walking accessibility, defined as the ease to reach essential destinations in the walk-in catchment area, may affect property prices as residents are likely to be willing to pay for this attribute. In addition, different destination categories may have differing influencing directions and magnitude. These two hypotheses are tested in this study. Taking Xiamen, China as a case study, we estimate cumulative opportunities of public services on foot, and develop a set of hedonic pricing models, more specifically, two pre-specified OLS, four Box-Cox transformed (non-spatial) models, and four spatial econometric models, to estimate, whether and to what extent, walking accessibility contributes to price premiums. Using a database of 22,586 second-hand residential properties in 358 multi- or high-story residential complexes, we find that: walking accessibility contributes to the variations in housing prices and accessibility to public services plays a role in determining housing prices; different services have vastly differing, even opposite, influencing impacts; walking accessibility to primary schools, commercial facilities as well as sports and cultural center have positive effects on house prices while walking accessibility to comprehensive hospitals adversely affects housing prices. Methodologically, we find that spatial econometric methods does improve estimation accuracy and has more explanatory power as compared to the standard models. The robustness check analysis furthers guarantees the plausibility of this study.

Keywords: capitalization effect; walking; cumulative opportunity; hedonic pricing model; spatial autocorrelation

1. Introduction

Walking is a low-carbon and sustainable non-motorized mode, beneficial to both individuals and the community (Plaut, 2005; Agrawal and Schimek, 2007; Guan and Ewing, 2017). It requires the physical activity of human beings, increasing fitness and health, facilitating social participation and boosting community livability (Guo and Loo, 2013). Moreover, walking is important for accessing local facilities and transit (Banister and Bowling, 2004). Furthermore, walking can be popular among residents and enables them to access various destinations and opportunities with ease when built environment is well planned and has some good attributes (e.g., 5 Ds, see Ewing and Cervero (2010); Lefebvre-Ropars et al. (2017)). Therefore, developers and residents both highly desire some degree of walking accessibility for their properties, which can be defined as the ease to reach essential desired destinations in the walk-in catchment area of a property.

Enhancing walking accessibility to public services is in general desirable, and residents may be willing to pay for this property attribute (Litman, 2003). A widely-used, well-accepted and publicly-available walking accessibility measure is Walk Score, which was developed in July 2007. Its algorithm combines around 10 variables of accessibility to amenities within the walk-in catchment area into a scale ranging from 0 (car dependent) to 100 (walker's paradise) (Carr et al., 2010). Generally, a few studies have been devoted to teasing out the association of Walk Score with property prices, and nearly all of the works suggest that properties with higher Walk Score command significant price premiums (Cortright, 2009; Pivo and Fisher, 2011; Rauterkus and Miller, 2011; Li et al., 2015).

Walking accessibility to differing public service categories, however, may affect housing prices differently, in both influencing directions and magnitudes. Being a single indicator, though easy to interpret, Walk Score has an inherent shortcoming: failure to fully capture users' preference for a broad spectrum of amenities. As Gilderbloom et al. (2015, p. 22) present, "neighborhood walkability is heavily tied to the number and variation of amenities or destinations available within a short walking distance". To wit, properties with the same Walk Score can have vastly different amenities within the walk-in catchment area. For example, adding one school or one entertainment facility into the walk-in catchment area contributes to the same magnitude of increase in the score, since the two amenities carry the same weight in its calculation. However, these two amenities may have remarkably differing influencing impacts on property prices. Furthermore, some of the destination categories considered for Walk Score calculation may not be deemed as amenities (Li et al., 2015). That is, some amenities (e.g., parks, school) can generate positive externalities for nearby properties, thereby increasing the prices. Residents may have a high willingness to pay for proximity to these amenities. Moreover, some categories have negligible or very marginal effects on property prices due to their relatively insignificant roles in residents' lives.

Other than Walk Score, travel impedance and gravity-based accessibility measures have been used in the studies devoted to teasing out the relation between accessibility and property prices. However, the cumulative opportunity (or isochronic) measure, a basic accessibility measure, is rarely used to measure walking accessibility. Generally, this approach counts the number of potential services and opportunities that can be reached within the constraints of a pre-determined travel time or distance (Vickerman, 1974). An inherent drawback is searching distance/time threshold setting. Yet, it is an appropriate and suitable measure which can be chosen to represent walking accessibility to public services, which can reflect the ease to reach service facilities in walk-in catchment area of a property since the value of walking distance/time threshold is undoubtedly acknowledged (e.g., half a mile, 0.9 km).

Public services may not always exert positive effects on nearby housing prices. Attributable to the nuisances such as pollution, noise, vibration and radiation, some kinds of public services (e.g., hospital, airport, cell phone station) may negatively influence nearby housing values. Proximity to them would result in a price penalty. There is a paucity of empirical evidence concerning the capitalization effects of walking accessibility to public services based on the cumulative opportunity measure. Moreover, few studies have incorporated spatial econometric techniques. In light of the above, we look at urban China where, to date, on the one hand there have been few empirical studies on quantifying price premiums attributable to walking accessibility; on the other, there have been severe concerns over walkability as with exploding ownership, private automobiles rapidly and excessively encroach sidewalks, open spaces, etc. (Cao, 2017; Wang and Zhou, 2017). The focuses of this study are *evaluating walking accessibility* and *pricing (or estimating the value of) walking accessibility*. As such, we generate the walk-in catchment areas of properties in ArcGIS and use the cumulative opportunity approach to measuring walking accessibility to four categories of public services of each property. Our cumulative-opportunity-based measure seems to be better reflect the diversity and number of available amenities. We then calibrate a set of functional forms, more specifically, two pre-specified hedonic pricing models, four Box-Cox transformed models, a spatial lag model (SLM) and spatial error model (SEM), both of which incorporate spatial effects, to comparatively evaluate the capitalization values of walking accessibility to public services and to see which model allows us to get the most reliable estimated values. Finally, a two-stage regression analysis further guarantees the robustness of our key findings.

The potential contributions of this paper include: (1) applying the cumulative opportunity approach to measuring walking accessibility to desired destinations, which was inspired by Carr et al. (2011), who have scrutinized the relationship between Walk Score and cumulative-opportunity-based accessibility to amenities. (2) quantifying the walking accessibility impacts on housing values in a context where few studies on the same topic have undertaken and gaining a more thorough understanding of capitalization effects. (3) comparing how different models perform when they are used to quantify those impacts and providing a few insights concerning the usefulness of spatial econometric models in evaluating the impacts of walking accessibility on housing prices. (4) offering some evidence for the implementation of value capture schemes for financing public service investments.

The remainder of this paper proceeds as follows. The ensuing section (Section 2) briefly reviews the relevant literature. Section 3 introduces the hedonic pricing model, Box-Cox transformation, and spatial econometric models, discusses shortcomings of the standard hedonic pricing model and describes the necessity of employing the spatial econometric methods; Section 4 introduces the study area and data, and describes independent variables for hedonic pricing modeling; Section 5 presents the modeling results while Section 6 draws conclusions and points out avenues for future research.

2. Related studies

We first briefly review diverse accessibility definitions and metrics, as well as accessibility applications in property valuation studies. Then, we synthesis the pertinent studies on the connection between property prices and Walk Score, the extensively-employed walking accessibility measure.

2.1. Accessibility metrics and applications in property valuation studies

Accessibility is a famous and extensively-studied concept in many fields like transportation, urban planning, and geography, but it does not have a unified and unambiguous definition, which hinges on the problem and context (Kwan, 1998). A host of selected definitions are summarized in Table 1. Notably, accessibility is thought to be influenced “by the qualities of the transport system (reflecting the travel time or the costs of reaching a destination) on the one hand and by the qualities of the land-use system (reflecting the qualities of potential destinations), on the other hand” (Straatemeier, 2008, p. 128).

Table 1

Selected definitions of transport accessibility

Definition	Source
the potential of opportunities for interaction	Hansen (1959, p. 73)
the ease with which any land-use activity can be reached from a location using a particular transport system	Burns and Golob (1976, p. 175)
the freedom of individuals to decide whether or not to participate in different activities	Burns (1979, p. 1)
the ease with which activities may be reached from a given location using a particular transportation system	Morris et al. (1979, p. 92)
the ease of reaching places	Cervero (1996, p. 1)
the number of activities which can be reached from a certain location	Geurs and Ritsema van Eck (2001, p. 19)
the extent to which land-use and transport systems enable (groups of) individuals to reach activities or destinations by means of a (combination of) transport mode(s)	Geurs and van Wee (2004, p. 128)
the ease of reaching valued destinations	Sun et al. (2017, p. 442).

Besides the diversity of definitions, accessibility measures are rather diverse as well, including but not limited to, travel impedance (travel distance/time, and monetary cost), cumulative opportunity, gravity-based measures, utility-based measures and constraints-based measures. Notably, the cumulative opportunity measure can be regarded as a special case of gravity-based approach, which counts the number of potential opportunities within a pre-determined catchment area, and indeed incorporates both a transportation component and an activity component. It emphasizes the number of potential opportunities within the region concerned instead of their distances, since all opportunities within the region are weighted equally, regardless of differences in travel impedance and attractiveness, and other opportunities not within the region are ignored (Handy and Niemeier, 1997). The model can be mathematically expressed as:

$$A_i = \sum_j \alpha_{ij} O_j ,$$

where A_i is the accessibility at point *i*, O_j is the opportunity (or activity) in zone *j*, and α_{ij} is a dummy variable, equals to 1 if zone *j* is within the predetermined area of point *i* and 0 otherwise.

The cumulative opportunity measure is, yet, rarely used in hedonic studies, to the best of our knowledge. Indeed, despite the diversity of modeling metrics, most of existing hedonic studies only the three (particularly due to its practical simplicity): (1) "nearest opportunity" approach: minimum time or distance (impedance) of reaching the nearest activity from residences (e.g., Andersson et al., 2010, 2012); (2) "all or nothing" approach: introducing an independent variable (0 or 1) within a predetermined area (e.g., So et al., 1997). (3) "gravity-based" approach (e.g., Cervero and Susantono, 1999; Ibeas et al., 2012). But this measure is comparatively less used since its modeling results are difficult, if not impossible, to interpret. Notably, the accessibility applications in hedonic literature are not as sophisticated as those in pure accessibility modeling studies (e.g., two-step floating catchment area method, individual-level utility-based method), since the main focus of hedonic studies is not accessibility itself, but the economic value of accessibility.

2.2 Walk Score and property prices

Some studies have been tested the effect of Walk Score on property prices, of which most have shown that higher Walk Score does command property price premiums. The earliest contribution can be traced to the work of Cortright (2009), who finds that the positive relationship between walk score and property prices in 13 of 15 housing markets in the United States and a 1-point increase in Walk Score increases values by $700–3000. Moreover, the author indicates that the price premium offered by walkability is higher in more populous metropolitan areas and those with more extensive transit services.

Pivo and Fisher (2011) observe that Work Score is positively related to prices of offices, retail and residential property values in the United States, while it cannot significantly affect the industrial property prices. They further present that an additional 10-point increase in Walk Score was associated with between a 1-9% increase in values. Similarly, Rauterkus and Miller (2011) discover that there is a positive relation between Walk Score and residential land values in Jefferson County, Alabama, and the premiums seem to be larger in more walkable neighborhoods. Li et al. (2014, 2015) note in their study of Austin, Texas that Walk Score had generally positive effects on values of condominium and single-family properties in neighborhoods that are already walkable. In a similar vein, Gilderbloom et al. (2015) find that walkability does bolster residential property prices in Louisville, Kentucky, and proposes a host of policy insights for encouraging the development of more walkable and sustainable communities. Yet, Boyle et al. (2014) show strikingly different results. Using a fixed effects regression model instead of an ordinary least squares (OLS) model, they demonstrate that Walk Score is too weak to affect housing value in Miami, Florida, after controlling for heteroscedasticity and neighborhood-specific fixed effects. And they further suggest that a possible reason for this is that more walkable areas tend to be more developed. Note that, Walk Score is available in very limited countries (United States, Canada, Australia, and New Zealand) only nowadays, which partially explains why most of, if not all, the relevant Walk Score studies are based on the United States setting.

3. Methodology

3.1 Hedonic pricing model

Hedonic pricing model is a popular method used to explain prices of properties in terms of their own characteristics. The main assumption of hedonic price theory is that implicit price (or utility) for each attribute of a property can be inferred by observing an individual's willingness to pay for each unique bundle of attributes (Cao and Hough, 2012). Most commonly, implicit or shadow values of the attributes of a property can be singled out and estimated from a regression equation using the OLS method.

The hedonic pricing model regresses property prices (Y) onto a set of observable property attributes (Xs) (e.g., size, proximity to the city center) as it assumes that heterogeneous properties are valued for their attributes. It can be mathematically expressed as:

$$Y = X\beta + \varepsilon,$$

where β is a vector of parameters associated with the explanatory variable, ε is the random error term that reflects the unobserved variations in property prices. It has a few basic functional forms, such as linear, semi-log, and double-log. The linear function is usually avoided, as the assumption of constant marginal implicit prices is not tenable in most of, if not all, the cases. Non-linear models are generally preferred.

3.2 Box-Cox transformation

Due to the lack of *a priori* economic theory which dictates a correct specification of the hedonic pricing model, the validity of any pre-specified model can be, indeed, questioned and challenged. As such, more flexible models can be derived for consideration using the Box-Cox transformation (Lai et al., 2006). The Box-Cox transformation is a typical nonlinear regression technique, which uses an iteration process which maximizes the model log-likelihood (Shyr et al., 2013). It can account for nonlinearity in model parameters and make the residuals more closely normal and less heteroskedastic. Box-Cox models have a variety of functional forms, such as the simple left-hand-side model, simple right-hand-side model, simple both-side model and separate both-side model. The technique has been widely employed in existing hedonic studies (Andersson et al., 2010, 2012; Shyr et al., 2013; Lai et al., 2006).

3.3 Spatial econometric models

Since the standard hedonic pricing model fails to that accounts for the presence of spatial dependence (spatial autocorrelation), employment of spatial econometric models becomes an obvious trend in real estate valuation and econometrics research (Krause and Bitter, 2012). In this vein, spatial econometric methods can be regarded as the advanced versions of hedonic pricing model. The main motivation of spatial modeling is to take into account of "near and related things" (Osland, 2010, p. 291). Thus, if spatial autocorrelation is present, failing to use spatial regression models will lead to biased and inconsistent coefficients. Employing spatial econometric models improves the reliability of our findings and conclusions. To the best of our knowledge, using the traditional OLS regression for spatial data is not as acceptable as before. Actually, the academia has used the OLS and traditional hedonic modeling less and less, largely as a result of the development of spatial econometric methods that can be estimated easily with growing computer power. Moreover, an ongoing diffusion of Geographic Information Systems (GIS) greatly eases the process of incorporating spatial dimensions into the analysis, thereby paving the way for the development of spatial modeling. The spatial lag model (SLM) and spatial error model (SEM) are two kinds of celebrated methods incorporating spatial dependence (Anselin, 1988).

3.3.1 Spatial lag model

The SLM is tolerable for the observed value of nearby observations (Osland, 2010) and its formula is:

$$Y = \rho WY + X\beta + \varepsilon,$$

where W is an exogenous spatial weight matrix that specifics the structure of the spatial relationship among observations, and information on which observations are considered neighbors and how their values are related to each other, which based on either contiguity or distance. The dimensions of a spatial matrix (N×N) are based on the sample size (N). This spatial weight matrix is based on either contiguity or distance. WY is the spatially lagged dependent variable to incorporate spatial autocorrelation effects. ρ is normally called the spatial dependence, spatial correlation or spatial autoregressive parameter. If $\rho = 0$, the SLM becomes the standard hedonic pricing model.

The SLM can be expressed as:

$$(I - \rho W)Y = X\beta + \varepsilon.$$

This formula indicates that the independent variables (Xs) are explaining the variation in the dependent variable (Y) that cannot be explained by the neighbors' values. That is, the marginal effect on property prices consist of both a direct effect (due to the change in the amount of the attribute) and an induced effect (due to marginal changes related to the neighbors' values) (Osland, 2010).

3.3.2 Spatial error model

Unlike the SLM which incorporates spatial effects via spatial lagging of the dependent variable (i.e., spatial auto-regression), the SEM deals with spatial autocorrelation in the error terms specifically. By specifying a global spatial autoregressive process in the random error term, the formula is as follows:

$$Y = X\beta + \varepsilon,$$
$$\varepsilon = \rho W \varepsilon + u,$$

where u is an error term whose distribution is assumed to be normal with zero mean and have fixed variance, ρ is the spatial dependence parameter which filters out the spatial autocorrelation in the error term. If λ equals 0, the SEM becomes the standard hedonic model.

4. Data and variables

4.1 Study area

This study was conducted on Xiamen Island, the central city of Xiamen. Xiamen City is in Fujian Province, China, and located on the southeast coast of China. It has a permanent population of 3.92 million and a total administrative area of 1699.39 km^2 as of 2016 (Xiamen Statistics Bureau, 2017). The city is bestowed with stunning natural scenery, livable environment, and has the strongly advancing economy (Xu et al., 2017).

Xiamen Island is the earliest urban area of Xiamen and has been the central city of Xiamen until now. It is made up of Siming District and Huli District, owning a total of nearly 130 km^2 land. There are three reasons why to choose Xiamen as the study context. First, a major limitation of hedonic pricing model is omitted variable bias. An effective approach to circumvent this problem is focusing on a narrow geographic area where a host of confounding variables can be properly controlled (Brasington, 2003). The scale and geographical settings of the island make it a tractable laboratory to conduct this research. Second, in the island, walking mode split is 33.4% (Zhou et al., 2011), which is comparable to the average value across China (34%) (Lu et al., 2009). This figure is much higher than that of many countries, such as the United States (10.4%) (Department of Transportation, 2011), England (25%) (Department for Transport, 2016) and New Zealand (12.4%) (Ministry of Transport, 2017). In these contexts, people have to heavily rely on the automobile (Wong et al., 2017, 2018), and cannot access various opportunities with ease, particularly due to the low-density urban development pattern. Finally, Xiamen tops in the walkability ranking among a total of 36 most developed and advanced cities in China (NRDC and SATU. 2017). This obviously implies that walking is attractive in this area.

4.2 Data

Asking price data were collected from one of the largest real estate agency websites of China, *Soufang.com*. A total of 22,586 second-hand housing units in 358 multi- or high-story residential districts were randomly sampled in late March 2017. It is noteworthy that no real estate laws, regulations, incentives and policy measures were introduced by the city government during the data collection period. Moreover, coordinates data from the government website or Google Earth are used to establish the GIS database of Xiamen Island, including urban morphology (e.g., water, green spaces), public services, road networks, bus stops and BRT stations.

4.3 Variables

Table 2 contains a description and descriptive statistics of variables. Walking distance threshold value is set to 900 meters because we follow the observation that pedestrians are only suitable for walking for no longer than 15 minutes because of their limited tolerance on physical burden (Wang et al., 2013). The distance threshold value is calculated as the product of the average speed (1m/s) and tolerable walking time threshold (15 min). The potentially contributory public services considered in this paper are primary schools, local shopping centers, hospitals, and sports and cultural centers. Additionally, property attributes such as size, age, neighborhood dummies, and proximity to a variety of geographical elements were controlled for. It is worth noting that in order to account for varying marginal contribution of the number of bedrooms to property value and impart more flexibility, we used dummies instead of a single discrete variable (number of bedrooms), following Malpezzi (2003) and Guo et al. (2014).

Table 2
Variable definitions and descriptive statistics

Variable	Description	Mean	Std. Dev
Dependent variable			
Price	Price of a property (10^4 Yuan in RMB)	767.08	513.34
Control variables			
Size	Floor area (m^2)	135.12	71.01
Age	Physical age of a property	10.33	5.91
Building height	Number of stories	20.11	11.66
Bedroom2-	Dummy variable, 1 for a property with 1 or 2 bedrooms, 0 otherwise	0.26	0.44
Bedroom3	Dummy variable, 1 for a property with 3 bedrooms, 0 otherwise	0.4	0.49
Bedroom4+	Dummy variable, 1 for a property with 4 or more bedrooms, 0 otherwise	0.34	0.48
Distance to the city center	Euclidean distance to the central point of Zhongshan Road (km)	7.17	3.01
Distance to sea	Euclidean distance to sea (km)	2.66	1.37
Distance to Wuyuan Bay	Euclidean distance to lake (km)	4.42	2.6
Distance to Airport	Euclidean distance to Xiamen Internation Airport (km)	5.57	1.92
Distance to BRT	Euclidean distance to the nearest BRT station (km)	1.55	1.11
School district	Dummy variable, 1 for a property within the	0.13	0.33

	attendence zone of a high-quality school, 0 otherwise		
Adjacency to elevated roads	Dummy variable, 1 for a property within 0.5 km of elevated roads, 0 otherwise	0.23	0.42
Residential district environment	Residential-district-level fixed effects dummy variable, 1 for a property in the residential district environment with good environment, 0 otherwise	0.64	0.48
Population density	Neighborhood fixed-effects variable (10^3/km^2)	16.80	9.60
Employment density	Neighborhood fixed-effects variable (10^3/km^2)	15.98	16.29
Bus frequency	Neighborhood fixed-effects variable (1/hour)	7.88	0.72
Bus stop	Number of bus stops within 0.5 km	6.37	4.03
Explanatory variables			
#PS	Number of elementary schools within the walk-in catchment area	1.53	1.52
#SC	Number of shopping centers within the walk-in catchment area	1.49	2.66
#H	Number of class 2A and 3A comprehensive hospitals within the walk-in catchment area	0.23	0.62
#SCC	Number of sports and cultural centers within the walk-in catchment area	0.10	0.32

5. Results

A pair-wise correlation analysis was undertaken to identify the association between variables, and its results are shown in the tables in the Appendix. The result suggests that correlations between different variables are low and multi-collinearity is not a problem in this study.

5.1. OLS regression

Two sets of functional forms (semi-log and double-log) were estimated using the OLS method. Table 3 provides the results. The double-log model is shown to outperform the semi-log model. It uses natural logs for variables on both sides of the proposed econometric specification. A practical advantage of this functional form is that the interpretation of the regression coefficients is rather straightforward. The coefficients of the regression function correspond to average attribute elasticities. Noted that, ten independent variables (bedroom 3, bedroom 4+, residential district environment, bus stop, school district, elevated road, and four walking accessibility measures) are not transformed as they are not strictly positive.

The explanatory power of the double-log model is adequate and reasonably high: it can explain 90.7% of the variations in property prices. This confirms that the twenty-one attributes we used have captured most of the variations in property prices. Furthermore, the signs of all variables are consistent with our expectations. All variables are significant at the 1% level in the double-log model.

Table 3
Results of the two pre-specified OLS models

Variable	semi-log OLS model		double-log OLS model	
	coefficient	t-statistic	coefficient	t-statistic
Size	0.005*	145.86	0.909*	194.28
Age	-0.017*	-40.64	-0.064*	-27.94
Building height	0.003*	14.93	0.064*	22.75
Bedroom3	0.310*	76.00	0.056*	13.60
Bedroom4+	0.403*	72.85	0.122*	21.49
Distance to the city center	-0.042*	-17.97	-0.109*	-24.26
Distance to sea	-0.096*	-56.11	-0.080*	-29.34
Distance to Wuyuan Bay	-0.043*	-15.05	-0.065*	-27.84
Distance to airport	0.017*	11.38	0.065*	11.72
Distance to BRT	-0.085*	-37.88	-0.072*	-29.92
School district	0.076*	14.38	0.074*	15.86
Adjacency to elevated roads	-0.077*	-15.51	-0.080*	-16.94
Residential district environment	0.177*	29.92	0.162*	31.35
Population density	-0.002*	-7.41	-0.029*	-8.80
Employment density	0.001*	9.27	0.013*	9.52
Bus frequency	0.019*	7.08	0.249*	13.81
Bus stop	0.008*	11.24	0.006*	8.91
#PS	0.012*	9.34	0.009*	7.92
#SC	0.002*	2.90	0.008*	11.14
#H	-0.020*	-6.85	-0.037*	-14.13
#SCC	0.002	0.32	0.018*	3.68
Constant	6.145*	181.81	1.608*	31.30
Performance statistics				
R-squared	0.8796		0.9065	
Adjusted R-squared	0.8794		0.9064	

Note: * Parameters are significant at the 1% level.

5.2. Box-Cox transformation

Four Box-Cox functions are estimated with the intention of further evaluating the robustness of variables. It should be noted that the ten untransformed variables are the same as above. Table 4 shows the Box-Cox transformation results and reveals that the most flexible form, the separate both-side Box-Cox model, outperforms other three Box-Cox models as well as the two OLS models. The levels of statistical significance of all variables are fairly consistent in all model specifications. This implies that our developed hedonic pricing models (both pre-specified and Box-Cox transformed) can explain price variations well and the variables included do affect housing prices. In addition, the signs of all coefficients are in line with expected.

Table 4
Results of Box-Cox transformed functional forms

Variable	Simple LHS model		Simple RHS model		Simple both-side Box-Cox model		Separate both-side Box-Cox model	
	coefficient	t-statistic	coefficient	t-statistic	coefficient	t-statistic	coefficient	t-statistic
Size	0.024**	169.30	5.975**	194.60	1.026**	196.24	0.334**	198.15
Age	-0.076**	-41.32	-10.606**	-27.53	-0.098**	-29.79	-0.076**	-34.94
Building height	0.013**	15.02	0.990**	5.35	0.079**	21.20	0.036**	18.37
Bedroom3	1.100**	61.16	-11.846**	-3.24	0.078**	12.30	0.140**	24.76
Bedroom4+	1.518**	62.24	10.175*	2.05	0.179**	20.34	0.204**	25.76
Distance to the city center	-0.206**	-19.73	-43.534**	-20.37	-0.159**	-23.83	-0.112**	-22.02
Distance to sea	-0.455**	-60.10	-77.298**	-50.44	-0.135**	-32.45	-0.142**	-41.87
Distance to Wuyuan Bay	-0.200**	-15.86	-39.739**	-15.46	-0.099**	-26.46	-0.083**	-22.52
Distance to Airport	0.060**	9.32	5.423**	4.02	0.082**	10.47	0.055**	10.24
Distance to BRT	-0.368**	-37.24	-42.203**	-20.81	-0.122**	-31.56	-0.133**	-35.92
School district	0.308**	13.27	28.394**	6.01	0.111**	15.24	0.101**	15.23
Adjacency to elevated roads	-0.357**	-16.23	-51.661**	-11.55	-0.132**	-18.07	-0.121**	-18.46
Residential district environment	0.738**	28.27	74.205**	14.00	0.244**	30.20	0.222**	30.00
Population density	-0.009**	-8.28	-1.879**	-8.43	-0.038**	-8.89	-0.019**	-8.48
Employment density	0.006**	11.00	1.328**	11.27	0.023**	11.75	0.018**	15.08
Bus frequency	0.128**	10.63	48.114**	19.17	0.331**	13.51	0.166**	11.41

Bus stop	0.031**	9.22	1.644*	2.44	0.009**	8.64	0.009**	10.09
#PS	0.053**	9.04	6.769**	5.70	0.016**	8.62	0.018**	10.94
#SC	0.011**	3.15	2.557**	3.58	0.011**	10.43	0.008**	7.75
#H	-0.083**	-6.35	-10.516**	-3.98	-0.055**	-13.60	-0.045**	-12.01
#SCC	0.035	1.45	23.619**	4.84	0.031**	4.17	0.025**	3.75
Constant	13.852**	92.92	233.816**	9.00	1.712**	23.19	4.137**	76.64
LHS	0.236**	40.30			0.070**	11.12	0.058**	9.65
RHS			0.986**	120.57			0.282**	29.90
Performance statistics								
R-squared	0.8900		0.8510		0.9071		0.9104	
Adjusted R-squared	0.8899		0.8508		0.9070		0.9103	

Note: **Parameters are significant at the 1% level. *Parameters are significant at the 5% level.

5.3. Spatial regression

A piece of spatial data analysis and modeling package, GeoDa, was employed to develop the spatial econometric models which take account of the spatial dependence in the data, using the maximum likelihood method. A Moran's I test was conducted to test for spatial effects first. Its results provide strong evidence of the existence of spatial autocorrelation (the *p*-value is less than 0.05). Table 5 reveals the modeling results and indicates that both outperform the six non-spatial models. Among them, the SEM is slightly superior to the SLM.

In the SLM, the spatially lagged dependent variable is positive and significant at the 1% level. This confirms the presence of spatial autocorrelation in the dependent variable and implies the positive adjacency effects: the price of a specific property depends on the prices of nearby properties, thereby justifying the use of spatial econometric techniques. In the SEM, the spatial dependence parameter is positive and significant at the 1% level as well, which illustrates that housing price is affected by not only the included independent variables but also the error of the nearby locations. Table 5 also presents that parameter estimations using spatial regression are different from those using OLS. This clearly demonstrates that ignoring spatial effects would lead to biased estimates.

In both spatial econometric models, all variables are significant at the 1% level. All control variables exhibit the expected signs. Generally, size, building height, number of bedrooms, distance to airport, school district, residential district environment, employment density, bus frequency, and bus stops have positive impacts on property prices, while building age, distance to the city center, sea, Wuyuan Bay and BRT stations, adjacency to elevated roads, population density have negative impacts. In addition, the coefficients of bedroom dummies show a non-linear pattern, which justifies the use of dummies. Moreover, the city center has a much greater effect than sea, Wuyuan Bay, airport and BRT stations on housing prices, which is indicated by a much larger distance elasticity. This agrees with the land-rent theory put forward by Alonso (1964). The negative signs indicate that as distance to the city center (or lakes, Wuyuan Bay, BRT stations) decreases, the property value increases, all else being equal. Yet distance to airport is found to have positive impacts on housing prices, which is logical and representative of reality. Generally, airports are regarded as NIMBY (not in my back yard) facilities, particularly attributed to nuisances (e.g., noise) (Cohen and Coughlin, 2008).

Table 5

Regression results of the spatial econometric models

Variable	SLM		SEM	
	coefficient	t-statistic	coefficient	t-statistic
Size	0.905**	194.34	0.903**	205.73
Age	-0.063**	-27.48	-0.082**	-27.13
Building height	0.060**	21.45	0.034**	11.71
Bedroom3	0.058**	14.29	0.040**	11.21

Bedroom4+	0.123**	21.75	0.082**	16.17
Distance to the city center	-0.111**	-24.86	-0.130**	-22.68
Distance to sea	-0.081**	-29.98	-0.057**	-16.30
Distance to Wuyuan Bay	-0.064**	-27.52	-0.072**	-22.76
Distance to Airport	0.062**	11.40	0.113**	14.79
Distance to BRT	-0.071**	-29.62	-0.043**	-15.39
School district	0.071**	15.26	0.072**	10.94
Adjacency to elevated roads	-0.078**	-16.66	-0.066**	-10.40
Residential district environment	0.157**	30.48	0.171**	25.63
Population density	-0.028**	-8.52	-0.032	-7.01
Employment density	0.014**	10.63	-0.002**	-1.08
Bus frequency	0.253**	14.12	0.276**	10.69
Bus stop	0.006**	8.63	0.006**	7.11
#PS	0.009**	7.53	0.006**	3.85
#SC	0.007**	10.22	0.012**	12.29
#H	-0.035**	-13.55	-0.038**	-10.81
#SCC	0.017**	3.49	0.013*	1.96
Constant	1.582**	30.98	1.690**	25.63
ρ	0.009**	15.76	0.538**	88.66
Performance statistics				
R-squared	0.9075		0.9335	
Log likelihood	5016.11		7748.97	
AIC	-9986.21		-15453.90	

Note: ** Parameters are significant at the 1% level. * Parameters are significant at the 5% level.

The estimation and interpretation of the coefficients associated with four walking accessibility measures are of primary interest here. All accessibility measures are highly robust and significant in nearly all model specifications. This greatly guarantees robustness and plausibility of our findings. We find solid evidence that walking accessibility to four public services concerned is associated with housing prices and significantly contribute to explaining housing price differences. Indicated by the signs of their coefficients, residential properties near more primary schools, shopping centers and sports and cultural centers, are more expensive, *ceteris paribus*. Somewhat surprisingly, better accessibility to high-level comprehensive hospitals is associated with lower housing prices. This result is consistent with the results of (Huh and Kwak, 1997; Peng et al., 2015). One possible explanation is housing buyers' age heterogeneity. Obviously, different age groups have dissimilar needs of health care services. Generally, elderly people are more likely to go to hospital (Szeto et al., 2017), so they may tend to live close to hospitals for convenience. In contrast, young adults seldom go to hospital, so they might not take into account proximity to hospitals when making residential choices. They even tend to live far away from hospitals. Another possible explanation is dis-amenity effects of hospitals. Generally, it is crowded around high-level comprehensive hospitals. In hospital-adjacent regions, there are too many people and vehicles. They generate noises and air pollution, thereby reducing nearby residents' quality of life (Peng et al., 2015).

In light of strong evidence of the existence of spatial autocorrelation, our preferred estimation model is the SEM, of which the estimated parameters can be directly interpreted. The coefficients associated with #PS, #SC, and #SCC (corresponding elasticities) are 0.006, 0.012, and 0.013, respectively. This demonstrates that for every primary school, shopping center and sports and cultural center within walk-in catchment areas, housing prices are 0.6%, 1.2%, and 1.3% higher, all else held equal. Furthermore, the coefficients associated with #H are -0.038, which indicates that for every comprehensive hospital within walk-in catchment areas, housing prices are 3.8% lower, *ceteris paribus*.

5.4. Estimation of walking accessibility elasticity

Table 6 tabulates the estimated elasticity using the double-log model and the two Box-Cox transformed models. The estimation using differing model specifications is fairly consistent. This reveals not only the robustness of our key findings but also that of the simple regression using double-log approach. The to-primary-school walking accessibility elasticity is relatively high, ranging from 0.014 to 0.019, followed by to-shopping-center walking accessibility elasticity, varying from 0.008 to 0.011.

Table 6
Estimation of walking accessibility elasticity

	Double-log LOS model	Simple both-side Box-Cox model	Separate both-side Box-Cox model
#PS elasticity	0.014	0.015	0.019
#SC elasticity	0.011	0.011	0.008
#H elasticity	-0.008	-0.008	-0.007
#SCC elasticity	0.002	0.002	0.002

5.5. Two-stage regression for robustness check

Though the abovementioned results (consistent and significant estimates across model specifications and consistent elasticity estimates) have greatly guaranteed the robustness of our key findings, we decide to undertake a two-stage regression analysis for further robustness check, which has been applied in other studies, for example, the work of Rauterkus and Miller (2011). We first regress the dependent variable (LogPrice) onto the seventeen control variables, and hypothesis that these attributes cannot fully explain property prices since they do not take walking accessibility into account. Then, in the second stage, we regress the residuals acquired from the first-stage regression onto the four walking accessibility variables. Table 7 shows the results of the two-stage regression. Walking accessibility measures are significant at the 1% level, which indicates that they do contribute to explaining a portion of the remaining variability in property prices. Moreover, the signs and magnitudes of both explanatory and control variables are consistent with the abovementioned model specifications.

Table 7
Results of two-stage regression for robustness check

Variable	First-stage: dependent variable = LogPrice		Second-stage: dependent variable = Residuals	
	coefficient	t-statistic	coefficient	t-statistic
Size	0.912	194.03		
Age	-0.066	-29.01		
Building height	0.073	26.45		
Bedroom3	0.055	13.29		
Bedroom4+	0.122	21.44		
Distance to the city center	-0.104	-25.27		
Distance to sea	-0.077	-30.18		
Distance to Wuyuan Bay	-0.062	-27.70		
Distance to Airport	0.051	9.62		
Distance to BRT	-0.074	-32.15		
School district	0.065	14.53		
Elevated road	-0.081	-17.68		
Residential district environment	0.141	28.30		
Population density	-0.026	-8.55		
Employment density	0.017	12.66		
Bus frequency	0.242	13.86		
Bus stop	0.005	8.50		
#PS			0.006	6.26
#SC			0.006	10.99
#H			-0.030	-13.33
#SCC			0.016	3.76
Constant	1.618	32.80	-0.012	-5.63
Performance statistics				
R-squared	0.9052		0.0106	

Adjusted R-squared	0.9051		0.0105	

Note: All parameters are significant at the 1% level.

6. Conclusions and discussion

Walking accessibility to desired destinations is assumed to affect property prices, while walking accessibility to differing service categories may affect housing prices differently, in both influencing directions and magnitudes. The studies devoted to investigating the connection between housing prices and Walk Score, the widely-used walking accessibility measure, can answer the former question, but not the latter. Additionally, current property valuation works generally employ three accessibility metrics (i.e., "nearest opportunity" approach, "all or nothing" approach, "gravity-based" approach). The cumulative opportunity approach has been rarely adopted, while it is very suitable to measure walking accessibility.

Based on 22,586 observations in Xiamen, China, we apply the cumulative opportunity method to walkability dimensions and develop a set of both non-spatial and spatial hedonic pricing models to estimate walking accessibility capitalization effects. We find the following: the externality of public services has been capitalized into housing prices and public services do confer accessibility benefits generally; public services within a walking distance do command price premiums, and residents are willing to pay for the walking accessibility; walking accessibility to some of public service categories has a positive effect on house prices: for every primary school, commercial facility and sports and cultural center within a walking distance, housing prices are 0.6%, 1.2%, and 1.3% higher, all else held equal; walking accessibility to comprehensive hospitals negatively affects housing prices, and hospitals are perceived as dis-amenities within this context: for each within a walking distance, housing prices are 3.8% lower, *ceteris paribus*; the spatial econometric methods outperform the standard hedonic pricing models for the studied problem. The robustness check analysis further guarantees the plausibility of this study. Our findings lend credence to policies encouraging land use changes that will lower distances from where people live to where they conduct activities.

Generally, walking accessibility enhancement increases housing values. In this study, "value creation" has been clearly identified. The next issue worth discussing is "value capture". However, nowadays, in urban China, due to institutional limitations such as lack of property tax and capital gains tax, residents can benefit from improvements in urban amenities without any cost. In the future, the municipal government is suggested to explore revenue sources and design policy tools to recoup a share of the value added by infrastructure provision so as to (at least partially) recover the initial capital costs, which conforms to the beneficiary-pays principle. However, in China, urban land is owned by the state instead of individuals. Land's lease revenue covers infrastructure cost nowadays, which partially explains why both land and property values are surprisingly skyrocketing in China (Zhao, 2014). But understandably, this single instrument is not adequate, especially for sites being re-developed. How to capture the windfalls (or value gains) using economically efficiency, socially equitable and administratively feasible revenue-generating techniques (e.g., tax increment financing, taxation of development uplift, special assessment districts delineation, development impact fees, joint (spatially coincidental) development of large-scale public services and adjacent properties) (Zhao et al., 2012) should be extensively discussed and explored in the coming years. Additionally, adjacent property rent is likely to go up as well together with the increase in property value, which consequentially increases labor cost and reduces disposable income, thereby lowering the competitiveness of local enterprises (compared to those in other cities). A tentative strategy is to decrease the tax rate of selected enterprises (possibly according to their respective tax contributions) and design suitable tools to pay the decreased taxes back to employers of these enterprises, which helps increase their employees' salary and disposable income.

Comprehensive hospitals are found to decrease nearby property values and be, arguably, deemed as dis-amenities within the context, possibly attributed to nuisances (e.g., noise, congestion, air pollution). This leads to social inequity unavoidably. The joint construction of comprehensive hospitals with other compatible amenities (e.g., urban park, green space) which produce price premiums is suggested. The amenities are on the one hand expected to lower the negative effects induced by comprehensive hospitals and on the other hand could create some buffer zones between the hospitals and nearby neighborhoods and recreation room for both patients and residents therein.

The walking accessibility price premium herein may be provided by not only *ease of access to amenities* but also *facilitation of casual encounters among residents*, as walkable neighborhoods are perceived as having high potential to improve social trust and community commitment (Kwon et al., 2017). A more sophisticated study (e.g., including an interaction variable describing the simultaneous influence of walking accessibility and face-to-face interaction) can be undertaken to test this hypothesis in future research.

There are still room for improvements in our studies. Due to data unavailability, some variables (e.g., income or education level of neighborhood, floor level) were not included in our models. In China, many databases are proprietary, owned by either governments or corporations. It is very difficult or, in some cases, even impossible to get access to the data for the public.

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APPENDIX

See Tables A1 and A2

Table A1

Correlation matrix variables codes

Variable	Code
Size (log)	C1
Age (log)	C2
Building height (log)	C3
Bedroom3	C4
Bedroom4+	C5
Distance to the city center (log)	C6
Distance to sea (log)	C7
Distance to Wuyuan Bay (log)	C8
Distance to Airport (log)	C9
Distance to BRT (log)	C10
School district	C11
Elevated road	C12
Residential district environment	C13
Population density (log)	C14
Employment density (log)	C15
Bus frequency (log)	C16
Bus stop	C17
#PS	E1
#SC	E2
#H	E3
#SCC	E4

Table A2
Correlation matrix

	C1	C2	C3	C4	C5	C6	C7	C8	C9	C10	C11	C12	C13	C14	C15	C16	C17	E1	E2	E3	E4
C1	1.00																				
C2	-0.36	1.00																			
C3	0.32	-0.58	1.00																		
C4	-0.04	0.14	-0.13	1.00																	
C5	0.67	-0.27	0.25	-0.59	1.00																
C6	0.06	-0.24	-0.05	-0.01	0.06	1.00															
C7	-0.30	0.06	-0.16	0.04	-0.24	0.04	1.00														
C8	-0.19	0.41	-0.14	-0.01	-0.11	-0.67	0.22	1.00													
C9	0.18	-0.14	0.41	0.00	0.11	-0.31	-0.17	0.23	1.00												
C10	-0.02	0.15	-0.29	0.02	-0.01	0.35	-0.24	-0.12	-0.42	1.00											
C11	0.05	-0.11	0.16	0.03	0.00	-0.11	0.03	0.08	0.21	0.03	1.00										
C12	-0.01	-0.15	0.14	0.01	0.00	-0.15	0.17	0.05	0.41	-0.57	0.15	1.00									
C13	0.42	-0.43	0.28	-0.06	0.29	0.19	-0.28	-0.28	0.25	-0.05	0.01	0.02	1.00								
C14	-0.32	0.26	-0.22	0.08	-0.25	-0.32	0.49	0.32	-0.03	-0.11	0.28	0.32	-0.26	1.00							
C15	-0.32	0.33	-0.32	0.11	-0.27	-0.19	0.37	0.23	-0.01	0.12	0.24	0.19	-0.25	0.62	1.00						
C16	-0.18	-0.08	-0.14	-0.03	-0.07	0.04	0.38	-0.06	-0.22	-0.15	-0.02	0.25	-0.10	0.33	0.38	1.00					
C17	-0.36	0.44	-0.20	0.07	-0.26	-0.42	0.23	0.48	-0.10	-0.11	0.01	0.10	-0.79	0.31	0.27	0.07	1.00				
E1	-0.20	0.25	0.23	0.02	0.12	0.04	0.32	0.14	0.36	0.27	0.06	0.25	0.33	0.27	0.18	0.07	0.18	1.00			
E2	-0.11	0.03	0.17	-0.02	-0.05	-0.36	0.19	0.22	0.26	-0.37	0.10	0.47	-0.20	0.42	0.37	0.33	0.30	-0.03	1.00		
E3	-0.04	0.10	0.03	0.01	0.02	0.37	0.00	0.18	0.22	0.12	0.23	0.20	0.04	0.26	0.21	0.14	0.09	0.22	0.29	1.00	
E4	0.01	0.01	0.04	0.03	0.03	0.14	0.06	0.02	0.06	0.08	0.16	0.13	0.04	0.15	0.08	0.03	0.12	-0.13	0.02	0.08	1.00