The Effects of Urban Redevelopment on Housing Prices in Shenzhen

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Abstract

This study investigates the effects of urban redevelopment on housing prices, based on the case of Shenzhen. Two different hedonic model specifications are applied, Ordinary Least Squares (OLS) and Spatial Lag Model (SLM). From the modeling results, we found that untreated urban redevelopment sites post significant negative impacts on adjacent housing prices and anticipated or actual redevelopment can alleviate this negative effect. Based on the hedonic models, we established a decision support framework for the planning of urban redevelopment in Shenzhen.

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1. Introduction

Urban redevelopment has long been recognized as a means for sustainable utilization of urban land resources. In western countries, the focus of urban redevelopment is placed on the renewal of brownfields. A brownfield site is "any land or premises which has previously been used or developed and is not currently fully in use, although it may be partially occupied or utilized. It may also be vacant, derelict or contaminated" (Alker et al., 2000: p. 64). The process of deindustrialization has left a legacy of brownfield sites in urban areas. In China, besides brownfields, urban redevelopment also endeavors to renew urban villages. Urban villages, a result of China's dual land system, are constantly criticized for their unregulated houses and messy street profiles. Consequently, as local governments are eager to achieve their ambition of building "world-class cities", these negative characteristics associated with urban village make it the focus of urban redevelopment in Chinese cities.

During the past two decades, urban redevelopment has received increasing attention from the government in China. For instance, the Chinese central government just released the Special Plan for the Revitalization of Old Industrial-Base Cities (2013-2022) in 2013. One of the central focuses of this planning is the transformation of problematic, formerly industrial urban areas. The implementation of this planning is expected to lead to the development of policies and the allocation of considerable funds. However, compared with the magnitude of sites waiting to be redeveloped, the funds allocated are never enough. As noted by De Sousa et al. (2009: p. 96): "A key barrier to brownfield redevelopment that is consistently identified in the literature is the lack of funding support, and a main barrier to attracting funding is the lack of information about the benefits that brownfield projects generate".

Using hedonic pricing model, this paper firstly investigates the effects of urban redevelopment on housing prices in Shenzhen, China. Considering the possible presence of spatial autocorrelation (SA), besides ordinary least squares (OLS), we also apply a spatial hedonic method: spatial lag model (SLM). We then propose a conceptual framework, in which the hedonic model is integrated into a planning support methodology for the simulation of economic effects of urban redevelopment projects. This research will significantly contribute to future policy-making concerning urban redevelopment issues. Planners can apply this decision support methodology to estimate the economic effects of different scenarios of urban redevelopment. Quantifying the benefits of urban redevelopment will also encourage greater investment on urban redevelopment projects and thus implement sustainable urbanization.

2. Literature Review

The hedonic price method is derived from Lancaster's (1966) consumer theory and Rosen's (1974) theoretical model. It considers that goods or services can be seen as a bundle of characteristics or attributes and are valued for these characteristics (Rosen, 1974). Generally, these inherit attributes are classified into structural attributes, neighborhood attributes and locational attributes (accessibility). One of the most important structural variables is floor area. In addition, age of house, floor level, number of bathrooms and bedrooms are also frequently used in hedonic models (Hamilton and Morgan, 2010; Hu et al., 2014). Neighborhood quality can be related to both characteristics within the neighborhood and those outside but in proximity to the neighborhood (Hu et al., 2014). Chau and Chin (2003) classified neighborhood characteristics into three categories: socio-economic characteristics (social class of the neighborhood, occupations of the inhabitants); local government or municipal services (schools, hospitals); and externalities (crime rates, traffic noise). The influence of accessibility on housing prices has long been recognized in the literature (McMillan et al., 1992; Palmquist, 1992; Ridker and Henning, 1968). Accessibility is often interpreted as accessibility to public transport, accessibility to workplace, and accessibility to various urban amenities such as open spaces.

Ever since its introduction, extensive research has been undertaken using hedonic pricing model to analyze the impacts of environmental dis-amenities on property values. Kaufman and Cloutier (2006) used a hedonic pricing model to investigate the effects of two brownfield sites and a park on adjacent residential property values and found that the redevelopment of the brownfields into greenspaces would result significant increase in surrounding residential property values. De Sousa et al. (2009) analyzed the impact of brownfield projects on nearby property values before and after the redevelopment and the results showed that 'the spillover effect of raising surrounding property values is significant in both quantity and geographic scope'.

It is generally recognized that property values are closely related to the values of their neighbors. Therefore, the consideration of SA is necessary in hedonic price model. In the presence of SA, the use of OLS estimation might cause biased results, since the fundamental OLS assumptions of independent and identically distributed error terms are violated (Mihaescu and vom Hofe, 2012). Whereas the majority of previous researches on the impact of brownfields on adjacent property values, for instance the research of Kaufman and Cloutier (2006) and De Sousa et al. (2009), applied an aspatial hedonic pricing model, without taking into consideration the effect of SA. There are two basic ways for handling SA in a standard hedonic model: the SLM and the spatial error model (SEM). The SLM assumes that the sales prices of proximate homes are correlated with one another, so the model includes a spatial lag variable to capture this effect. The SEM assumes that the error terms of the hedonic model are spatially autocorrelated (Kelejian and Prucha, 1998).

By comparing OLS and SEM, Ihlanfeldt and Taylor (2002) modeled the effects of hazardous waste sites on the prices of surrounding commercial and industrial properties. The results of both models showed a statistically significant reduction in property values. Svetlik (2007) evaluated the impacts of local brownfields on residential property values by using both SLM and SEM to account for SA. He found a positive relationship between distance from brownfield sites and property values, and he also concluded that SLM and SEM results are more reliable than OLS results. Mihaescu and vom Hofe (2012) estimated the impacts of brownfield sites on the value of single-family residential properties. They used three different hedonic model specifications, OLS, SLM, and SEM. Model diagnostics indicated that the two spatial hedonic model specifications are superior to the OLS specification, and the results showed that properties located within 1000 feet from a brownfield site experience a significant depreciation in the values. Using both OLS models and spatial hedonic models, Mhatre (2009) estimated the impacts of Superfund sites on surrounding single-family residential properties before and after remediation. He found that housing prices significantly increased with the increase in distance to the nearest contaminated Superfund, and after remediation this negative impact declined.

From existing literature, we notice that although the application of hedonic model (both spatial and aspatial) in the investigation of untreated brownfields on adjacent housing prices is extensive, only a handful of studies have tried to shed light on the change of effects after redevelopment, by also taking into account of SA. Since urban redevelopment is largely a practice of sustainable urbanization, from the practical point of view, it is essential for a better understanding of the benefits of redeveloping activities. Therefore, more work is needed to improve the knowledge of economic effects of urban redevelopment.

3. Study Area, Methodology and Data

3.1 Study Area

Shenzhen city is located in the southeast of China, which is well known as a typical fast-growing city. Ever since the central government of China designated Shenzhen as a special economic zone (SEZ) in 1979, the city has been growing at a rapid pace: the population increased from less than 20,000 people before 1979 to 10.4 million people in 2010 (SZBS, 2011). In 2010, the urban construction land of Shenzhen was 764 km^2, in contrast, the so called "san jiu" land (old urban areas, old factories, old villages) was up to 240 km^2. Due to the combination of rapid urbanization and limited land resources, Shenzhen has encountered an unprecedented development bottleneck. In this context, in 2004 the municipal government started exploring urban renewal policies. Ever since, a series of regulations as well as master plans have been enacted to manage urban redevelopment practices in Shenzhen, for instance, the Master Plan of Urban Villages Redevelopment (2005–2010), the Redevelopment Master Plan, and the Provisional Regulations of the Redevelopment Plan of Urban Villages in Shenzhen. In the year of 2010 alone, there were 93 urban renewal projects approved by the government. According to the data provided by the Urban Planning Land and Resources Commission of Shenzhen Municipality, in 2009, investment in urban renewal projects was RMB 6.72 billion, and in 2012, the amount had increased to RMB 25.07 billion. In the Special Plan for Sanjiu Land Redevelopment of Shenzhen (2010-2015), a total investment of RMB 350 billion has been budgeted for the planning period.

3.2 Methodology

In this study, we use both standard hedonic model (OLS) and spatial hedonic method to analyze the effect of urban redevelopment on adjacent housing prices in Shenzhen. Since SLM is an appropriate method for capturing spillover effects (Kim, Phipps, and Anselin, 2003), we use SLM as a spatial hedonic method. In this study, we chose the log-log form for all the variables calculated in distance (access to metro stations, access to job opportunities, and distance to nearest urban redevelopment site) and semi-log form for other variables.

The multivariate functional form of OLS model is as follows:

$$LN(\boldsymbol{P}) = \alpha + \beta\boldsymbol{S} + \gamma\boldsymbol{N} + \eta LN(\boldsymbol{A}) + \mu LN(\boldsymbol{U}) + \varepsilon \tag{1}$$

where *LN(**P**)* represents the natural logarithm of the transaction price of residential property; ***S*** represents structural house characteristics; ***N*** represents neighborhood characteristics; *LN(**A**)* represents the natural logarithm of the accessibility variables; *LN(**U**)* represents the natural logarithm of our focus variable distance to nearest urban redevelopment sites; α, β, γ, η and μ are associated parameter vectors; and ε is a vector of random error terms.

In accordance, the spatial hedonic model (SLM) is defined as:

$$LN(\boldsymbol{P}) = \alpha + \rho \boldsymbol{W} LN(\boldsymbol{P}) + \beta \boldsymbol{S} + \gamma \boldsymbol{N} + \eta LN(\boldsymbol{A}) + \mu LN(\boldsymbol{U}) + \varepsilon \quad (2)$$

where ***W*** is a row standardized n × n spatial weights matrix describing the connectivity of observations; ***WLN(P)*** represents the spatial lag of the dependent variable; ρ is the spatial autoregressive parameter.

Several issues are worth noting concerning the calculation of spatial weights matrix in this study. Firstly, in the literature, various ways for defining neighbors in spatial weights matrix can be generally classified into distance-based or contiguity matrices (having common borders) (Kim, Phipps, and Anselin, 2003). For distance-based methods, distance decay method and binary distance band method are the most widely used. In this study, we use the binary distance method to calculate spatial weights matrix, in which a cut-off distance is provided, and the non-diagonal elements are equal to 1 when d_{ij} (the distance from apartment i to apartment j) is smaller than the cut-off distance and 0 if otherwise. Secondly, the transaction price data is from apartments in large newly-built gated communities. A gated community is “a walled or fenced housing development with secured and/or guarded entrances” (Huang, 2006: p. 508). Gated communities might provide various amenities such as community parks and schools. In terms of housing prices, apartments within the same gated community tend to have very similar prices (Hu et al., 2014). Therefore, it would be ideal if one can define spatial connectivity according to the boundaries of gated communities. However, in practice, unless the largest distance between two apartments within the same community is smaller than the distance between any apartments in two different communities, the aforementioned ideal situation cannot be realized. Lastly, our data has one limitation: we do not have information about the location of every apartment, and we only have information on the boundary of every gated community and the location of the community’s main entrance. That is to say, in our data, apartments within the same gated community share the same location. However, when calculating spatial weights matrix, this limitation has enabled us to define spatial connectivity by the exact boundary of every gated community (by simply setting cut-off distance to 10 m). By this means, SA can be controlled for most effectively.

3.3 Data Collection

Apartment transaction data is from the database of Urban Planning Land and Resources Commission of Shenzhen Municipality. In order to ensure the significance of effects of urban redevelopment sites on property values, we selected those transactions within 2 km of urban redevelopment sites. In total, we obtained 6475 transactions in 2011, and 7287 transactions in 2014. These apartments are all located in large-scale newly-built gated communities. We focus on large-scale newly-built communities under several considerations: Firstly, new-build housing can avoid the effect of depreciation and thus makes our model more reliable; Secondly, as our research focuses on the impacts of urban redevelopment on housing prices, large-scale communities, with a substantial amount of apartments, can better reflect this spillover effect than small-scale communities; Lastly, compared with second-hand housing, the transaction price of new-build housing is relatively more real, since in China, it is very common that during the transaction of second-hand housing, in order to evade taxes, people will sign the so-called “yin-yang” (under-the-table) contracts and the price can be reported very low. To make the housing transaction data of different years comparable, we use the consumer price index (CPI) for new-build houses released by the National Bureau of Statistics of the People’s Republic of China to convert both price in 2011 and 2014 to price in 2010.

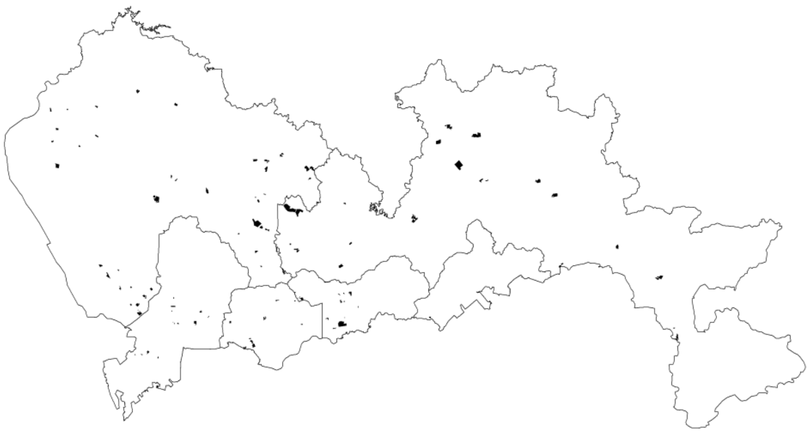

Fig. 1. Spatial distribution of 101 urban redevelopment sites (2012 to 2013)

The information of urban redevelopment projects is collected from the website of Urban Planning Land and Resources Commission of Shenzhen

Municipality[1]. From 2009, the municipal government of Shenzhen started to release the urban renewal plans on this website. From this website, we collected the information of 101 urban redevelopment projects from 2012 to 2013 (Fig.1). These urban redevelopment sites (URSs) can be classified into three categories: industrial site, urban village site, commercial and residential site. By 2014, some of the redevelopment plans have been implemented and some have not, thus with the transaction data of 2014 we can investigate the effect of anticipated or actual redevelopment on surrounding housing prices.

The information of dwelling attributes in our data includes floor area of the apartment, floor level, number of bedrooms and the degree of decoration (decorated or not). In China, the decoration status of apartments, especially new-build apartments, has significant impact on housing prices (Tian, 2006). After preliminary test, we found significant collinearity between floor area and the number of bedrooms. Therefore, we dropped the number of bedrooms as independent variable.

Since all the communities are newly built, socio-economic characteristics of the neighborhood such as income level, educational level, or occupations of the inhabitants are not (yet) likely to have effect on the prices. Therefore, we focus mainly on the physical characteristics of the neighborhood. We firstly chose greening rate of the neighborhood, school quality, proximity to beach, proximity to lakes and rivers, and proximity to urban villages. After preliminary analysis, we found that the greening rate and proximity to lakes and rivers have no significant effect on housing prices. Therefore, we dropped these two variables in the final model. School quality is an important factor affecting housing prices (Haurin and Brasington, 1996). In Shenzhen, the city is divided into different school districts and living in a good school district enables the access to high quality schools. We chose 31 school districts in 2011 and 33 school districts in 2014 which have high quality schools, and measured whether a community in located within these school districts or not. Since Shenzhen is a coastal city and proximity to the ocean is believed to have positive effect on neighborhood qualities. To capture this effect, we included proximity to beach (500 m) as an independent variable. Lastly, it is believed that the presence of urban villages would incur a disamenity effect on adjacent residential properties (Chen and Jim, 2010). Since Shenzhen is a city well-known for numerous urban villages, we consider the presence of urban villages (100 m) as an important variable.

Since we do not have location information of every apartment, all the accessibility variables are calculated on a neighborhood basis, which

[1] http://www.szpl.gov.cn/xxgk/csgx/ (last assessed in 20/02/2015)

means that there are no variations between apartments within the same neighborhood. To control for the possible impacts of lack of variations on modeling results, we decided to include as few accessibility variables as possible. It is also suggested in the literature that models should follow the principle of parsimony by using a small number of key variables (Butler, 1982; Mihaescu and vom Hofe, 2012) and that biases due to missing variables are small and have negligible prediction and explanatory power on the equation (Mok, et al., 1995). Eventually, we chose two accessibility variables: access to metro stations and access to job opportunities. We used route distance to calculate the accessibility and in the model these two variables are transformed into the negative value of the logarithm form.

For our focus variables, it is estimated that in 2011 the presence of URSs would pose negative impact on adjacent property values and in 2014 the anticipated or actual redevelopment would alleviate this negative effect or even generate positive effect on property values. Since it is the presence of URSs that will pose impacts on housing prices (Eiser et al., 2007; Mihaescu and vom Hofe, 2012), we calculated Euclidean distance to these URSs and in the model this variable is transformed into the logarithmic form.

Table 1 gives definition and descriptive statistics of the dependent and independent variables in the hedonic model.

Table 1. Descriptive statistics of the variables in the hedonic price model

Variable	Description	2011				2014			
		Minimum	Maximum	Mean	Standard deviation	Minimum	Maximum	Mean	Standard deviation
DEPENDENT VARIABLE									
LN_PRICE	Logarithm of gross price (10^4 RMB)	3.447	6.824	5.004	0.504	3.633	6.771	4.979	0.434
STRUCTURAL CHARACTERISTICS									
FLOOR	Number of floor level	1	49	15.805	8.134	1	47	15.440	9.743
AREA	Floor area of an apartment (m^2)	19.000	261.000	89.188	34.526	34.000	310.000	93.002	27.354
DECORATION	Dummy: 1 when an apartment is decorated	0	1	0.228	0.420	0	1	0.338	0.473
NEIGHBORHOOD CHARACTERISTICS									
SCHOOL	Dummy: 1 when an apartment is in a high quality school district	0	1	0.273	0.446	0	1	0.150	0.359
BEACH	Dummy: 1 when the beach is within 500 meters	0	1	0.011	0.103	0	1	0.033	0.177
VILLAGE	Dummy: 1 when there is an urban village within 100 meters	0	1	0.577	0.494	0	1	0.577	0.494
ACCESSIBILITY									
LN_METRO	The negative value of the logarithm of route distance to nearest metro station (m)	-9.315	-4.977	-7.647	0.941	-10.267	-0.363	-7.397	1.595

Table 1.(continued)

Variable	Description	2011				2014			
		Minimum	Maximum	Mean	Standard deviation	Minimum	Maximum	Mean	Standard deviation
LN_JOB	The negative value of the logarithm of route distance to nearest manufacturing enterprise (m)	-7.727	-1.808	-6.204	1.101	-7.831	-3.974	-6.416	0.861
FOCUS VARIABLE									
LN_URS	Logarithm of Euclidean distance to nearest URS (m)	2.106	7.599	6.235	1.134	0.693	7.549	6.012	2.000

4. Hedonic Model Results and An Integrated Decision Support Framework

4.1 Results

This section presents modeling results from both OLS and SLM specifications. Model diagnostics (Table 2) reveal that SLM is superior to the standard OLS model. The univariate global Moran's I of the dependent variable is 0.678 in 2011 and 0.700 in 2014, indicating the presence of strong SA in housing prices. In consequence, the results of OLS are biased, and our following discussion will focus on the results of SLM.

Table 2 Model diagnostics for OLS and SLM estimations

Diagnostics	OLS		SLM	
	2011	2014	2011	2014
R-squared	0.700	0.730	0.857	0.932
Log-likelihood	-853.922	526.497	1521.21	5504.34
Akaike (AIC)	1727.84	-1032.99	-3020.42	-10986.7
Schwartz (SC)	1795.6	-964.056	-2945.89	-10910.9

Table 3 Estimation results of OLS and SLM model specifications

Variable	OLS				SLM			
	2011 (n=6475)		2014 (n=7287)		2011 (n=6475)		2014 (n=7287)	
	Coefficient	Std.Error	Coefficient	Std.Error	Coefficient	Std.Error	Coefficient	Std.Error
Constant	5.738***	0.052	4.372***	0.028	1.432***	0.052	0.494***	0.022
FLOOR	0.006***	0.000	0.002***	0.000	0.004***	0.000	0.001***	0.000
AREA	0.010***	0.000	0.010***	0.000	0.007***	0.000	0.008***	0.000
DECORATION	0.152***	0.009	0.176***	0.007	0.027***	0.006	0.036***	0.003
SCHOOL	0.071***	0.008	0.219***	0.009	0.043***	0.006	0.049***	0.004
BEACH	0.315***	0.035	0.418***	0.019	0.024	0.024	0.031***	0.009
VILLAGE	-0.303***	0.008	0.008	0.006	-0.057***	0.006	-0.017***	0.003
LN_METRO	0.182***	0.004	0.086***	0.002	0.070***	0.003	0.019***	0.001
LN_JOB	0.059***	0.003	-0.038***	0.004	0.010***	0.002	-0.009***	0.002
LN_URS	0.026***	0.004	-0.014***	0.002	0.016***	0.003	0.002**	0.001
ρ					0.677***	0.006	0.758***	0.004

Note: Dependent variable is natural logarithm of gross price (converted to 2010 price).

* Significant at 90% level; ** Significant at 95% level; *** Significance at 99% level

Since the spatially lagged dependent variable ***WLN(P)*** in Eq.2 is endogenous to the model, the "true" effect of each independent variable β^T (taking structural variables for example) can be calculated as $\beta^T=(1-\rho)^{-1}\beta$ (Anselin, 2002; Feng and Humphreys, 2008). Therefore, we can calculate the total impacts based on coefficients in Table 3 (see Table 4).

Table 4 Total impacts from SLM results

Variable	2011		2014	
	Coefficient	Property value effect (%)	Coefficient	Property value effect (%)
FLOOR	0.012	1.207	0.004	0.401
AREA	0.022	2.224	0.033	3.355
DECORATION	0.084	8.763	0.149	16.067
SCHOOL	0.133	14.225	0.202	22.385
BEACH	0.074	0.000	0.128	13.655
VILLAGE	-0.176	-16.138	-0.070	-6.761
LN_METRO	0.217	24.234	0.079	8.220
LN_JOB	0.031	0.031	-0.037	-0.037
LN_URS	0.050	0.050	0.008	0.008

The results are generally consistent with the hedonic literature. For instance, structural characteristics such as floor level, floor area, and decoration are positively correlated with housing prices; within a good school district and access to metro stations are positively related to housing prices, whereas the presence of urban villages depreciates property values. However, we also get two interesting findings. In 2011, proximity to beach does not have significant effects on housing prices, which might due to poor access to the beach in 2011. Moreover, in 2014, job accessibility is negatively correlated to housing prices. Since our job opportunity data is from manufacturing enterprises, which often generate environmental problems such as noise and air pollution, with the increasing awareness of and demand for environmental quality as well as improvement in transportation infrastructure, people might be willing to pay more in order to live farther away from these enterprises.

In terms of our focus variable, the distance to the nearest URS is positively related to housing prices both in 2011 and 2014 ($p<0.01$ in 2011, $p<0.05$ in 2014). That is to say, before the announcement of urban redevelopment plans, if the distance to nearest URS increases by 10%, the housing price would increase by 0.5%. Whereas after the announcement of redevelopment plan or actual redevelopment activities, 10% increase in the distance to nearest URS only leads to 0.08% increase in housing prices. Therefore, the model captures a net effect of 0.42% on housing prices. For a house of RMB 1.66 million (the mean price of apartments in our sample), before redevelopment, the average reduction in market value for properties located within 2 km of an URS was approximately RMB 829, and total reduction for the pre-redevelopment sample would be RMB 5.37 million. While after the announcement of redevelopment plan or actual redevelopment activities, this discount in housing prices has decreased to about RMB 133, and RMB 0.97 million for the whole post-redevelopment sample. Our findings are similar to Mhatre's (2009) study, wherein significantly positive relations exist between housing prices and distance to the nearest contaminated Superfund in the pre-remediation model. The difference is that in Mhatre's post-remediation model, the effect of the nearest Superfund site is insignificant. Overall, both results imply reduction or elimination of the negative impact of URSs on surrounding property values.

4.2 A Decision Support Methodology for Urban Redevelopment in Shenzhen

It is noted by Kaufman and Cloutier (2006: p. 20) that "'Local officials' assessment of the viability of reclamation and redevelopment is, at least in part, dependent on the impact that redevelopment may have on property values and property tax revenues". Therefore, based on the spatial hedonic model, we develop a decision support framework for the planning of urban redevelopment in Shenzhen (Fig.2). Firstly, different scenarios of planning intervention can be designed. Each scenario contains information of URSs that are going to be redeveloped. After geocoding the URSs into GIS systems, all the houses within 2 km of every URS can be identified. From the housing input, we can obtain the value of our focus variable (Euclidean distance to nearest URSs) as well as structural variables (*FLOOR*, *AREA*, and *DECORATION*). With maps of good school district, beach and urban villages, we can calculate neighborhood characteristics (*SCHOOL*, *BEACH*, and *VILLAGE*). With public transportation map and road network map, we can calculate accessibility variables (route distance to the nearest metro station and route distance to the nearest job opportunity). Secondly, all the variables calculated are put into hedonic models to simulate the market value of properties. For house i, if we define P_{i_pre} as the housing price before redevelopment and P_{i_post} after redevelopment, the net effects of urban redevelopment on housing prices would be: $\Delta P = \Sigma (P_{i\_post} - P_{i\_pre})$. P_{i_pre} can be obtained from the pre-redevelopment model, and P_{i_post} can be calculated in the post-redevelopment model. ΔP can thus be calculated for each scenario. By comparing the net benefits with the estimated costs, all the scenarios can be evaluated, and based on which a final decision can be made. As aforementioned, quantifying the benefits of urban redevelopment can encourage greater investment on urban redevelopment projects and thus implement the revitalization of deteriorating communities.

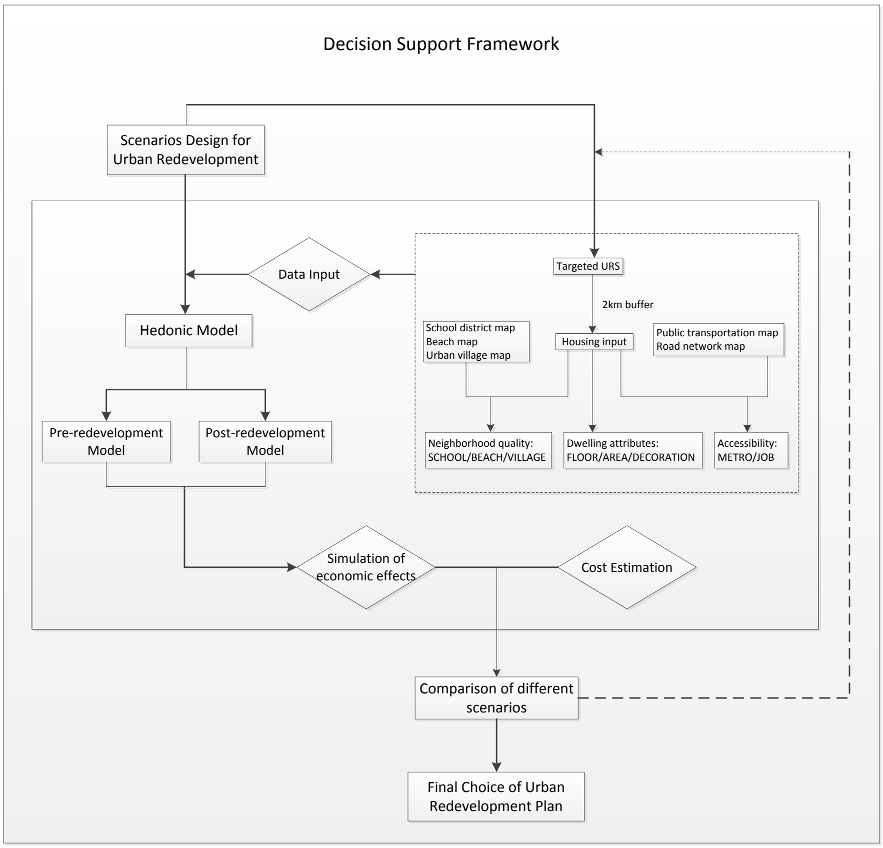

Fig. 2. Decision support framework for urban redevelopment

5. Conclusion

Urban redevelopment has been recognized as an important means of promoting sustainable urbanization. However, owing to inadequate information on the benefits of urban redevelopment projects, lack of funding support is always the main barrier for urban redevelopment practices. This study used hedonic price methods to investigate the effects of urban redevelopment on property values in Shenzhen. To take account of SA, we applied a spatial hedonic methodology. Results from SLM showed that before the announcement of urban redevelopment plans, if the distance to nearest URS increases by 10%, the housing price would increase by 0.5%; after the announcement of redevelopment plan or actual redevelopment activities, 10% increase in the distance to nearest URS only leads to 0.08% increase in housing prices. The results indicated that anticipated or actual redevelopment can alleviate the negative effect that untreated URSs posted on surrounding housing prices. Based on the hedonic models, we established a decision support framework for the planning of urban redevelopment. Under different scenarios of urban redevelopment, planners can use this decision support methodology to estimate the economic effects of urban redevelopment projects.

It is worth noting that the present study has several limitations. Firstly, we only investigated the effects of urban redevelopment on residential properties, whereas previous studies have also identified effects on commercial and industrial properties. Secondly, the benefits of urban redevelopment revealed in this study are relatively small, which might due to the fact that we were not able to distinguish actual redevelopment from anticipated redevelopment. It is believed that actual redevelopment will have greater impacts on housing prices. Lastly, our decision support methodology only takes into account the economic effects of urban redevelopment. No doubt that urban redevelopment projects will also generate substantial social impacts. Therefore, more comprehensive decision support methodologies should take into consideration both economic and social impacts.

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