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ESTABLISHING DYNAMIC IMPACT FUNCTION FOR HOUSE PRICING BASED ON SURRENDING MULTI-ATTRIBUTES: EVIDENCE FROM TAIPEI CITY, TAIWAN

Jieh-Haur CHEN[1,*], Li-Ren YANG[2], Vidya Trisandin AZZIZI[1], Eric CHU[1], Hsi-Hsien WEI[3]

[1] *Department of Civil Engineering, National Central University, Jhongli, Taiwan*
[2] *Department of Business Administration, Tamkang University, Tamsui, Taiwan*
[3] *Department of Building and Real Estate, The Hong Kong Polytechnic University, Hong Kong, PR China*

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Abstract. The objective of the research is aimed for a solution that is to establish the dynamic impact function of surrounding multi-attribute for house pricing. It is also able to measure the ripple effect and allows the hedonic parameter estimates to vary from point-to-point. A comprehensive literature review is carried out to obtain an adequate theoretical basis for the corresponding hypothesis and concepts. The proposed dynamic impact function for multi- attributes is then constructed based on the characteristics of surrounding facilities. Adopting the convenience sampling criteria of 95% confidence level on the data sampling and 10% limit of error in a 5–95% proportion, we collect the empirical data of 39 yearly house sales in the investigated urban areas of Taipei city focusing on housing prices and then utilize them for evaluating and adjusting the function. The actual house price and that of proposed function affected by Mass Rapid Transit (MRT) stations are analysed, resulting in the correlation coefficient at 0.946 (single attribute) and 0.944 (multi-attribute), respectively. The findings support that proposed function can highly represent the house pricing pattern and be an accurate tool for appraisers.

Keywords: house pricing theory, impact function, multi-attribute, financial engineering, property management.

Introduction

Over the last few years, the Taiwan government has applied a new policy regarding property tax within the real estate domain which has had a considerable impact on the Taiwan real estate market. The possible turnover index for the period from 2003 to 2005 had dropped from its original peak of 136.77 to 121.38. Furthermore, because of this property tax, some construction companies are reluctant to build new properties (Bahmani-Oskooee & Wu, 2018). Even the ones that have already started a project may be reluctant to complete it, because after completion, the contractor has to bear a huge tax burden even prior selling it. These circumstances have caused many investors to withdraw from the real estate market. The proportion of customers who buy their own homes or their own real estate has increased. The Ministry of the Interior's real estate platform has identified the following trend: the rate for residential demand for the first half year was 43%. The change of housing demand accounted for 42%, with an increase of 4.7% in the second half of the year. This was the highest within the last five years, previously the rate had never gone above 4% (Bahmani-Oskooee & Wu, 2018). Consumers choosing self-built real estate take into account various factors such as the quality of housing, the surroundings, parking, traffic convenience, and so on. Despite the fact that accurate appraisals and consideration of impact factors have helped to improve consumer awareness of real estate prices, it is still difficult for them to assess the impact of different factors on real estate prices. There has been little on the accurate assessment of the impact of real estate impact factors, therefore consumers do not have any basis of reference to follow.

The rational and effective allocation of information as well as resource integration has only been used by real estate producers for determination of prices. Consumers and government departments also need to pursue this goal. Rosen introduced the Hedonic price theory in 1974, which became the main method to solve the pricing problem with a wide range of applications. In addition to its application in real estate analysis, it is also used in agricultural land use analysis, agricultural marketing, video game marketing, industrial product marketing, environmental

*Corresponding author. E-mail: *jhchen@ncu.edu.tw*

assessment, social welfare policy, housing pricing, and transport convenience as well as other measures (Bahmani-Oskooee & Wu, 2018). Most of the relevant research and analysis does not take into account the fact that real estate consumers belong to different categories, for example different ethnic groups, or that different external environmental conditions might need to be considered (Gu, 2018). Among them, the convenience of facilities for transportation has recently caught practitioners' attention and become one of the most important factors affecting housing prices, with access to Mass Rapid Transit (MRT) and train stations being the main facilities for consideration. Although the importance of major facilities such as MRT stations or train stations is clear, a complete assessment is still lacking (Wen & Chang, 2014; Taltavull de la Paz & McGreal, 2019; Zhang, Zhou, Hui, & Wen, 2019). Numerous real estate valuations were made using the "comparison approach" followed by the "parcel survey" strategy in the past. However, whether it is the parcel survey, comparison approach, or hedonic price method, each of them has its own advantages and disadvantages. Comparative methods for real estate analysis are similar to the strategies used for determination of building prices. After comparing and adjusting the relevant factors (individual factors, regional factors, and price data), the valuator arrives at the corresponding price in the real estate market. The advantage of this method is that it is responsive towards actual real estate market prices. The disadvantages are that a lot of time and labour is required to compare the relevant information, the method is not objective, and it is vulnerable to variations in market prices (Chen, Chien, & Lee, 2011). The cost method is simple and convenient but often cannot be used to determine prices when cost information is lacking, resulting in a discrepancy between the estimated price and the actual price (Gholipour, Al-Mulali, Lee, & Hakim, 2016; Gholipour & Lean, 2017). In order to analyse the impact for multi-facility characteristics, it is necessary to study the prices of a large amount of real estate. The most suitable appraisal method for this purpose is the hedonic price method. In this method, real estate is treated as a collection of various characteristics, in which each feature has some implied value. In recent years, as computer and information technology has progressed, a real estate transaction database has been established. The following topics must be considered when using the hedonic price method to assess real estate prices: (1) whether the characteristic value is regarded as either constant or log-linear (Li & Brown, 1980; Des Rosiers, Lagana, & Theriault, 2001; Kopczewska & Lewandowska, 2018; Jonkman, Janssen-Jansen, & Schilder, 2018; Mastromonaco & Maniloff, 2018; J. J. Zhang, Fu, Chen, Chu, & C. C. Zhang, 2018; Lee, Liang, Chen, & Tung, 2018). For example, the price and the distance from transportation are often regarded as linear or log-linear, but some transportation hubs such as busy MRT stations, or airports, can also be sources of noise pollution which could have a negative impact on housing prices. Given that negative and positive values are added at the same time, the influence is not always linear. (2) Another important consideration is taking into account the impact of environmental characteristics and quantity. Most studies have only considered the distance between public facilities and the real estate, but have not taken into account the impact of number of the public facilities. (3) Sales time: In real estate appraisal, the pricing date is an important factor because the tax rate corresponds to pricing date, as well as price index and degree of depreciation. In the absence of knowing the time of the sale, lack of comparative price information (e.g. cost and revenue data), and nonlinear influence by surrounding multi-attributes in a dynamic matter (e.g. MRT stations in metro area), real estate appraisal becomes incorrect thus rendering it impossible to analyse. Furthermore, although there are some methods discussing the spatial problem while using the hedonic concept, those methods cannot express or quantify the ripple effect by multi-attributes well (Zhang et al., 2019; Hill & Scholz, 2018; Lee et al., 2018; Wen, Chu, Zhang, & Xiao, 2018; Zhang et al., 2018). A dynamic mathematical function that can explain nonlinear impact by surrounding multi-attributes, measure the ripple effect, and provide relatively accurate assessment is important against the existing methods.

Considering the above-mentioned problems in an attempt to provide an effective solution for practitioners, we aim for a solution that is to establish the dynamic impact function of surrounding multi-attribute for house pricing. It is also able to measure the ripple effect and allows the hedonic parameter estimates to vary from point-to-point. The scope of this research is to study the impact of nearness to public facilities such as universities, libraries, arts centres, thrift shops, department stores, supermarkets, night markets, hospitals, police stations, fire departments, on housing prices. The convenience of location and nearness to public facilities as well as distance from business districts is usually measured by distance or time. Specifically, the hedonic price method is used to explore the impact of nearness to facilities such as MRT stations, parks, and stores on the housing prices within a region and to develop a price function using the characteristics of these facilities, generated by the impact curve equation.

1. Real estate appraisal and financial engineering theories

Information and methods regarding real estate price as well as the appraiser's expertise and experience play important roles in determining the economic value of real estate, especially in monetary terms (Badarinza & Ramadorai, 2018; Agyemang, Asamoah, & Obodai, 2018; Wen et al., 2018). To make reasonable and accurate judgements the appraiser must have sufficient information as well as professional knowledge and previous experience (Alexander & Barrow, 1994; Hill & Scholz, 2018). In practice, there are several methods often used by appraisers, those are the comparison approach, parcel surveying, income approach and hedonic price method. The main method used in this study is the hedonic price method. This pricing method is based on the real estate characteristics, where the price is calculated by taking into account the impact of different housing price characteristics. Real estate prices are affected by many different characteristics, such as supply and demand in the real estate market, the surrounding environment and other factors (Bahmani-Oskooee & Wu, 2018; Zhang & Yi, 2018; Wu, Sah, & Tidwell, 2018). These features are used to establish a feature function graph and sensitivity analysis of different influential factors is carried out. Due to different number of characteristics and combinations, there are a lot of possibilities regarding real estate pricing. The basic idea of this method is to decompose the product price to show the price implied by the various characteristics. Each characteristic is analysed and its impact on price change removed (Du, Wu, Ye, Ren, & Lin, 2018). The supply and demand factors are applied to determine the remainder of the price change (Gu, 2018). The partial function obtained for each characteristic variable of the function in a certain fixed period is required in order to find the impact of changes in the characteristics on real estate prices. In the absence of homogeneous data, it is possible to compare non-homogenous real estate prices between the initial and the reporting period (Hui, 2010; Antonakakis, Chatziantoniou, Floros, & Gabauer, 2018). Accordingly, the relationship between real estate prices and characteristic factors may be expressed as:

$$InV = \sum B_i InX_i + \sum r_j T_j + e, \quad (1)$$

where the variable in the equation are: V – housing price; X_i – housing characteristic factors; B_i – the relationship between the quality of the housing and housing price; T_j – housing in period j then $T_j = 1$, otherwise, $T_j = 0$; r_j – the price coefficient of change in the house price in j; e – random error variable.

Even for the same piece of real estate, different appraisers with different experience, professional knowledge may arrive different prices. Therefore, a method for reducing the differences between subjective appraisals and determining the impact of various factors on real estate prices has become an important topic in real estate appraisal. The International Association of Assessing Officers (IAAO) has pointed out that computer assisted mass assessment (CAMA) is now widely used to provide standardized procedures for real estate assessment, rather than simply using the computer to do data processing. Since 1996, computer-aided assessment has been promoted in a number of countries. CAMA has become an auxiliary tool for tax assessment (Bhargava, Wu, Lu, & Wang, 2004). In the United States, for example, computer assisted appraisal has been developed not only for the public sector, but also incorporated into an auxiliary mortgage credit automatic valuation model (AVM). In contrast to these technology-assisted valuation methods, traditional appraisal methods are still used to evaluate the different characteristics of real estate. Experienced appraisers draw upon their experience to complete different forms of appraisal accurately (Lean & Smyth, 2013). Scholars state that the characteristics affecting real estate prices can be divided into five categories. The first category is physical characteristics, the second category is location, the third category is financial factors, the fourth category is transaction costs, and the fifth category is the impact of inflation and prices. Physical characteristics include the number and quality of the buildings. Location includes the financial impact, economic externalities, and transportation costs. Financial factors refers to number of loans and affordability. Transaction cost refers to the cost of information acquisition and marketing time. Finally, the impact of inflation and named price refers to the price index. The second category is considered to greatly affect housing prices because of the impact of the surrounding facilities (Droes & Francke, 2018; Zhang et al., 2018). Similar studies can be also seen in examining the spatial relationship among environmental health factors, neighborhood amenities, and house prices (McCord et al., 2018; McCord, MacIntyre, Bidanset, Lo, & Davis, 2018). These considerations regarding parametric and non-parametric measurement can be regarded as factors that influence house prices based on distance.

2. YIMBY (Yes In My Back Yard) facilities

The provision of urban service facilities is important to local residents. Such facilities have a positive impact, the so-called "yes in my backyard effect" derived from their suitability, convenience, and other positive benefits (Liu et al., 2018). The proximity of such facilities has a certain degree of impact on residential prices. The establishment of objective assessment criteria is of considerable importance to the appraisal process. In terms of facilities, schools was used to have the greatest impact on housing prices, followed by large parks, department stores, MRT stations, large stadiums and convenience stores, because these facilities affect life in the surrounding area (Meen, 1999). However, because the trend in recent years has been for couples to have fewer children, the impact of schools has been significantly decreased (Des Rosiers et al., 2001). Transportation facilities have become one of the main considerations in the choice of homes but preferences vary. Facility utilization is affected by location factors. When the impact of certain surrounding facilities is too large, it weakens the degree of preference towards the facilities (Gu, 2018). It may even produce the opposite result (Oikarinen, 2008, 2014). Taking into account the current trend of real estate choices, this study takes MRT stations as the main facility.

3. Development of the dynamic impact function for house pricing

Although there are some methods discussing the spatial problem while using the hedonic concept, those methods may not express or quantify the ripple effect by multi-attributes well (Chen, Ong, Zhang, & Hsu, 2017; Zhang et al., 2019; Hill & Scholz, 2018; Lee et al., 2018; Wen et al., 2018; Zhang et al., 2018; Gu, 2018). Considering the above-mentioned problems in an attempt to provide an effective solution for practitioners, the mathematical equations for real estate pricing are built using financial engineering theory, specifically based on the hedonic price method. The proposed dynamic theory is then introduced for real estate analysis in order to find the influential characteristic factors and evaluate their impact on housing prices, before finally using a normal distribution curve method to deduce the curve of influence on housing prices given the afore-mentioned factors. The hedonic price equations are applied for real estate with similar factors such as category, age, area (pings), proximity to multi-facilities, and so on under the conditions that the target facilities are located at the centre. The dynamic impact function is established due to compare differences in distance between the real estate and target facilities. It must satisfy the following assumptions: (1) there are no other environmental factors affecting the area within facility perimeters; (2) no other YIMBY facilities are close to the target area where the facility is located; (3) individual independent asset performance of the dynamic price is based on the distance. The factors for the proposed dynamic impact function are discussed below.

Given that factors can generate noise or environmental pollution, being the closest to some types of YIMBY facilities (e.g., MRT stations, high-speed railway stations, highways), does not automatically mean that the price of nearby real estate is higher. In a regular hedonic price model, the peak price depends on the distance from facilities in the corresponding area. After reaching this peak, the YIMBY effect on housing prices begins to decline with distance. After a certain distance from the facilities, there is no longer any influence on housing prices in the surrounding area. Prices are relatively the same in other words there is in convergence of housing prices. Price convergence is case-by-case depending on the region as well as the influence of the facilities. Assuming that the proposed dynamic impact function *f(x)* fits the distance-decay and YIMBY effects; therefore, *f(x)* can be divided into three parts (functions A, B, and C) shown in Figure 1.

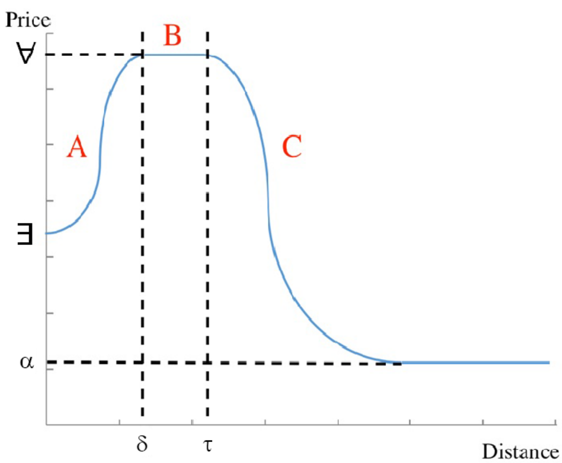

Figure 1. Proposed pricing model

It is asymmetric as Curve A increases, housing price rises from the initial level and then reaches the peak price at distance δ. Curve B is maintained at the same level as the peak price between δ and τ. Curve C shows the effect as a decline in prices from peak ∀, with the final convergence of housing prices occurring at α.

3.1. Derivation of the curve A function

Curve A is similar to the normal distribution curve, and the equation for Part A can be deduced from the normal distribution curve as follows:

$$y = \frac{1}{\sigma\sqrt{2\pi}} e^{\frac{-(x-\mu)^2}{2\sigma^2}}. \tag{2}$$

In the original equation y, $\sigma\sqrt{2\pi}$, $-(x-\mu)^2$, and $2\sigma^2$ are used to find the equation of the normal distribution curve. The location of the highest peak can be located using *y* and $-(x-\mu)^2$. The value of the x-coordinate of the highest peak is μ. The reciprocal $\sigma\sqrt{2\pi}$ affects the value of *y*, because of which σ affects the width of the graph. In Equation (2), σ affects the width of the graph, thus we can see $2\sigma^2$ as the main factor affecting the width.

The final distance from the facilities causes convergence of housing prices. Suppose the room rate price is α and in (2) item *y* is adjusted by $y - \alpha$. Converting both sides of the original normal distribution curve to a height of 0 for a convergent price α, results in the following equation:

$$y - \alpha = \frac{1}{\sigma\sqrt{2\pi}} e^{\frac{-(x-\mu)^2}{2\sigma^2}}, \tag{3}$$

where the maximum value of $e^{\frac{-(x-\mu)^2}{2\sigma^2}} = 0$ when the standard deviation σ is positive ($\sigma \geq 0$). At the same time the maximum value of $e^{\frac{-(x-\mu)^2}{2\sigma^2}}$ is 1. The maximum value of *y* can be deduced using $\frac{1}{\sigma\sqrt{2\pi}} + \alpha$. Assuming that the reciprocal of the difference between the highest peak price and house price difference is β, then $\sigma\sqrt{2\pi}$ can be converted to β. $\sigma\sqrt{2\pi}$ contains the value of the curve that can affect the size of the curve, therefore it can be seen that the peak price is equal to $\frac{1}{\beta} + \alpha$. The equation is as follows:

$$y - \alpha = \frac{1}{\beta} e^{\frac{-(x-\mu)^2}{2\sigma^2}}. \tag{4}$$

In the original normal distribution curve, μ denotes the *x* coordinate value of the highest peak point. Assuming that the distance between the property and "YIMBY" facility at the highest price in *f(x)* is δ, the original normal distribution curve equation μ is unlimited in scope. δ parameter indicates distance, therefore $\delta \geq 0$. Given these assumptions, the equation is as follows:

$$y - \alpha = \frac{1}{\beta} e^{\frac{-(x-\delta)^2}{2\sigma^2}}. \tag{5}$$

From the original normal distribution curve equation, we find that $2\sigma^2$ affects $\sigma\sqrt{2\pi}$ and vice versa, in terms of the height and width of the curve. In order to make the deductive target curve equation more consistent with the price curve presented by the *f(x)*, $2\sigma^2$ is assumed as *y*. The equation is derived as follows:

$$y-\alpha=\frac{1}{\beta}e^{\frac{-(x-d_1)^2}{\gamma}}. \quad (6)$$

Equation (6) is used to derive impact of the "YIMBY" facilities in the surrounding price curve function. Here x represents the distance between the property and the "YIMBY" facility, y indicates the price of the real estate. Because of the said x distance, its scope should be greater than or equal to 0. The meaning of each parameter on the price curve in relation to characteristics of the "YIMBY" facilities is defined below:

1. Parameter α is adjusted by the y value for the convergence of housing prices beyond a certain distance housing prices not affected by the facilities. By using the curve to reach the end of the convergence, we can control the final price convergence regarding the impact of the factors with parameter β affecting the price level ($\alpha \geq 0$).
2. Parameter β is derived by $\sigma\sqrt{2\pi}$ from the reciprocal of the highest price and the price difference convergence. The height of the curve can be controlled if adjusted to a single variable, because σ only affects the width of the curve ($\beta \geq 0$).
3. Parameter γ controls the width of the curve. The larger the curve is, the smaller the amount of γ should be. The width of the curve cannot be controlled because there are two equations (γ and σ) affecting each other.
4. Parameter δ indicates the highest price of the property and the distance between the housing area and the facilities ($\delta \geq 0$).

3.2. Derivation of the curve B function

It can be seen from Figure 1 that after the price reaches its peak, the peak price is maintained for some distance and then goes down before finally reaching convergence. The linear equation for finding the part B peak price can be derived by using the curve equation for part A. If $x = \delta$ in Equation (5) where the peak price rate can be obtained using $\frac{1}{\beta}+\alpha$, then the equation is as follows:

$$y=\frac{1}{\beta}+\alpha. \quad (7)$$

If $x = \delta$ to $x = \tau$, the peak price is $\frac{1}{\beta}+\alpha$.

3.3. Derivation of the curve C function

This curve function is derived based on the equation for the exclusion of dynamics. The equation is a simplified form of path formula as follows:

$$L(x)=\frac{N^2}{\frac{(l-x)}{\mu_0\mu_r S_1}+\frac{x}{\mu_0 S_2}} \quad (0\leq x\leq+\infty). \quad (8)$$

After derivation, the formula can be formulated as follows:

$$y=\frac{N^2}{\frac{l}{\mu_0\mu_r S_1}+\frac{(\mu_r S_1-S_2)x}{\mu_0\mu_r S_1 S_2}}. \quad (9)$$

Given the A equations, it is assumed that the prices will converge in α and Equation (6) converges to 0. The adjusted formula is as follows:

$$y-\alpha=\frac{N^2}{\frac{l}{\mu_0\mu_r S_1}+\frac{(\mu_r S_1-S_2)x}{\mu_0\mu_r S_1 S_2}}. \quad (10)$$

In (10), the maximum value occurs when $x = 0$, however the peak price of the curve is $x = \tau$. Thus, in Equation (8), x adjusted to $x - \tau$ as follows:

$$y-\alpha=\frac{N^2}{\frac{l}{\mu_0\mu_r S_1}+\frac{(\mu_r S_1-S_2)(x-\tau)}{\mu_0\mu_r S_1 S_2}}. \quad (11)$$

when $x = \delta + d_i$ has the maximum value of $\frac{1}{\beta}+\alpha$. N^2 is a constant, therefore it is set as 1. The relationship is as follows:

$$\frac{1}{\beta}=\frac{1}{\frac{l}{\mu_0\mu_r S_1}}, \quad (12)$$

where $\frac{l}{\mu_0\mu_r S_1}$ is assumed to be β. The equation is as follows:

$$y-\alpha=\frac{1}{\beta+\frac{(\mu_r S_1-S_2)(x-\tau))}{\mu_0\mu_r S_1 S_2}}. \quad (13)$$

where μ_0 is a constant. It is assumed that $\mu_0=1$ and $\mu_r S_1$ for θ, and S_2 as ε. The equation is as follows:

$$y-\alpha=\frac{1}{\beta+\frac{(\theta-\varepsilon)(x-\tau))}{\theta\varepsilon}}. \quad (14)$$

When $\theta > \varepsilon$, Equation (14) is convergent and $\frac{(\theta-\varepsilon)}{\theta\varepsilon}$ can control the distance to reach the convergence price. Derivation and integration of the above formula (6), (7), and (14), lead us to yield the dynamic impact function *f(x)*:

$$f(x)=\begin{cases}\frac{1}{\beta}e^{\frac{-(x-\delta)^2}{\gamma}}+\alpha, & 0\leq x<\delta\\ \frac{1}{\beta}+\alpha, & \delta\leq x\leq\tau\\ \frac{1}{\beta+\frac{(\theta-\varepsilon)(x-\tau)}{\theta\varepsilon}}+\alpha, & \tau<x<+\infty\end{cases}. \quad (15)$$

The value of α is always positive, because in house price convergence, the value of the house price is always greater than zero.

4. Implementation and discussion

The research has provided a solution that is to establish the dynamic impact function of surrounding multi-attribute for house pricing. It is also able to measure the ripple effect and allows the hedonic parameter estimates to vary from point-to-point. Thus, there are two implementations to evaluate the proposed function $f(x)$. The first one is to evaluate the proposed function using a single main facility that affects house prices. The other one is for multi-attributes (main facilities). The following conditions must be met: (1) there must be no other major impact factor affecting housing prices in the MRT area; (2) the main impact on housing prices in the area is proximity to MRT facilities; (3) there are no other MRT stations within a investigated range, so it is clear which MRT station acts as the main facility that affects house prices. After determining the area, the real estate locations are chosen using the Ministry of Interior real estate network transaction price inquiry service. The real estate is selected according to the following conditions, being similar in: (1) age; (2) size; (3) quality; and (4) terms of the reputation of the construction company that develops the real estate. After the selection of real estate cases around the MRT station, information regarding location of the transaction, real estate area, transaction price, price per unit, room and housekeeping patterns, as well as floor height is obtained using the Ministry of Interior real estate transaction data base. Other real estate related information is obtained using Google earth, such as date, house age, the time it takes for the house to be sold, access to parking, number of floors, and real estate category. Analysis of position, distance from the MRT station, as well as status quo is carried out using GIS and survey data. For the feature price impact function affected by a single and multiple factors (numbers of MRT stations), we conduct 4 case studies: Beitou MRT station (single factor), Jingmei MRT (single factor), Houshanpi-Kunyang MRT (2 factors), Dongmen-Zhongxiao-Xinsheng MRT (3 factors) stations in the investigated area based on convenient sampling. The prices of total 138 housing units sold in 2009 around investigated MRT stations are selected, which satisfies 95% confidence level on the data sampling and 5% limit of error in a 10–90% proportion (Chen & Hsu, 2008; Chen, Yang, Su, & Lin, 2010). The observations cover house sold data in the investigated area in a limited time period (May, 2009) in 2009. This can minimize the impact by force majeure such domestic macro-economy, global trade volatility, and major disasters. The reason to use past data is due to the data/case sensitivity themselves. It may influence house transactions/price if revealing latest information. For Case Study 1 and 2, they can be inferred as the significant factor because there are no other factors that affect the price of housing in the surrounding area. Beitou MRT station is located in the Taipei north region approximately 6 km away from downtown center and Jingmei MRT station is in the south side of the city, also approximately 6 km away from downtown center. For Case Study 3 and 4, Houshanpi-Kunyang MRT stations (2 factors) are approximate 1 km away from the main shopping district of Taipei and Dongmen-Zhongxiao-Xinsheng MRT stations (3 factors) are right at the most prosperous center of the city.

The chosen housing units sold from 3 to 7 years old are all located in the investigated regions. None of the chosen apartment buildings had first-floor storefronts, and the selected units are located on the 2nd to 10th floors. Each unit is between 30 and 60 pings (100 to 200 meter^2) in area. It can be seen that the theoretical house price curve is similar to the actual house price curve, and shows the same trend. The correlation between the two lines is analyzed using the distance between the actual housing unit and the MRT station. The CORREL (array1, array2) function in Microsoft Excel allows users to calculate correlation coefficient r by inserting the real price data and estimated price by the proposed function. The value of the correlation is between 1 and −1. The closer to 1 the greater the correlation, the higher the degree of similarity between the two curves, implying that the proposed function can be applied in practice. By inserting the dynamic impact function (Equation 15), the actual house price and the theoretical house price are analysed using the CORREL function in Microsoft Excel. Tables 1–3 show that all of their correlation coefficients $r > 0.9$ (0.946, 0.981, and 0.944 respectively).

Table 1. The actual distance and case prices affected by a single impact factor (Beitou MRT station, Taipei)

Observation	Distance (m)	Actual house price (million NTD/m^2)	Predicted house price (million NTD/m^2)
1	70	14.92	15.11
2	110	16.12	16.26
3	145	16.64	16.64
4	196	16.61	16.64
5	234	15.97	15.23
6	300	15.40	13.94
7	314	14.24	13.77
8	314	14.15	13.77
9	336	13.65	13.55
10	364	13.50	13.32
11	400	13.18	13.10
12	445	12.61	12.88
13	454	12.49	12.85
14	513	12.32	12.65
15	568	12.62	12.51
16	653	12.57	12.35
17	679	11.77	12.31
18	694	10.85	12.29
Correlation coefficient $r = 0.946$			

Table 2. The actual distance and case prices affected by a single impact factor (Jingmei MRT station, Taipei)

Observation	Distance from Jingmei MRT station (m)	Actual house price (million NTD/m^2)	Predicted house price (million NTD/m^2)
1	191	12.30	12.30
2	203	12.22	12.22
3	247	11.93	11.93
4	270	11.31	9.95
5	272	11.42	11.31
6	274	11.06	11.42
7	301	9.83	8.85
8	307	9.45	9.45
9	311	8.92	8.92
10	316	8.89	8.62
11	327	8.76	8.49
12	346	8.75	8.49
13	351	8.74	8.48
14	355	8.65	8.39
15	358	8.59	8.16
16	375	8.26	7.85
17	398	8.24	7.83
18	403	8.06	7.66
19	425	8.06	7.66
20	511	8.02	7.62
21	528	7.92	7.53
22	550	7.90	7.51
23	554	7.79	7.79
24	557	7.77	7.77
25	558	7.76	7.76
26	559	7.74	7.74
27	561	7.69	7.69
28	570	7.64	7.64
29	588	7.62	7.62
30	593	7.54	7.54
31	604	7.47	7.47
32	633	7.46	7.46
33	723	7.39	7.39
34	745	7.38	7.38
35	813	7.35	7.35
36	830	7.30	7.30
37	834	7.26	7.26
38	840	7.24	7.24
39	847	7.23	7.23
40	849	7.22	7.22
Correlation coefficient r = 0.981			

Table 3. Actual distance and case prices affected by multiple impact factors (2 factors)

Observation	Distance from Houshanpi MRT station (m)	Distance from Kunyang MRT station (m)	Actual house price ($million NTD/m^2)	Predicted house price ($million NTD/m^2)
1	1	1399	12.21	12.25
2	28	1373	12.73	12.72
3	66	1334	13.08	13.52
4	79	1321	13.79	13.79
5	248	1153	14.50	14.49
6	255	1145	14.46	14.49
7	263	1137	13.90	14.30
8	325	1075	13.23	13.27
9	431	969	12.70	12.59
10	431	969	12.64	12.59
11	525	875	11.33	12.31
12	665	735	11.57	11.50
13	831	569	14.44	13.67
14	861	539	14.39	14.05
15	900	500	14.82	14.82
16	965	435	14.67	14.82
17	970	430	13.69	14.82
18	1003	398	14.30	14.82
19	1188	213	14.12	14.54
20	1241	159	14.14	14.37
21	1395	5	13.28	13.75
Correlation coefficient r = 0.944				

Figures 2–4 illustrate the fitting between actual and predicting house sold price. For Case study 1, the presence of a park (Chengde Park) increases the quality of life in the surrounding area, making house prices higher than the theoretical curve, as indicated by results obtained after a field visit. It can be seen that the theoretical house price curve is similar to the actual house price curve, and shows the same trend. Accordingly, the findings indicate that it is the facility characteristics which affect the level of housing prices. It can be seen that there is a convergence of housing prices in the same area. For 3 or more attributes, assuming that there are N MRT stations affecting the same area, the dynamic function gives $f_1(x), f_2(x), f_3(x) \ldots f_N(x) f_1(x), f_2(x), f_3(x) \ldots f_N(x)$. Thus, N-1 should be summed and deducted from α. The aggregate is as formulated follows:

$$\sum_{i}^{N}\left[f_i(x)\right]-(N-1)\alpha . \qquad (16)$$

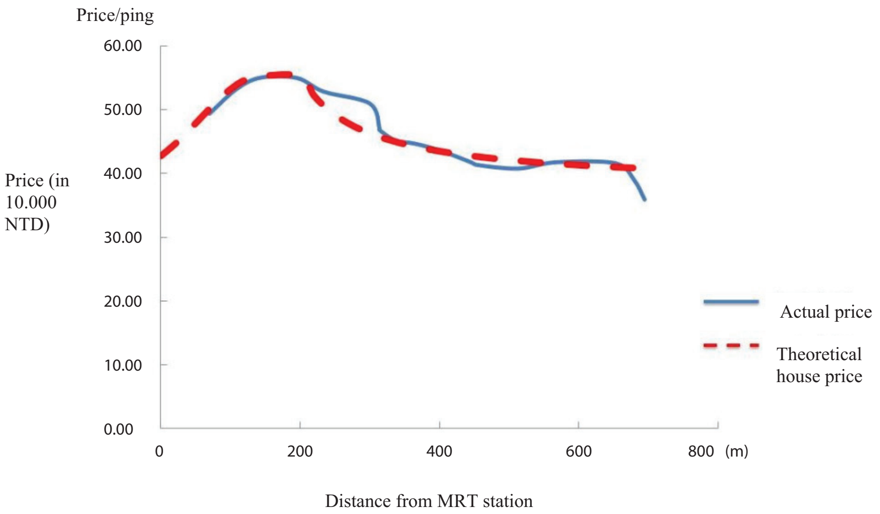

Figure 2. Comparison between theoretical and actual house price curve influenced by single factor (Beitou MRT station, Taipei)

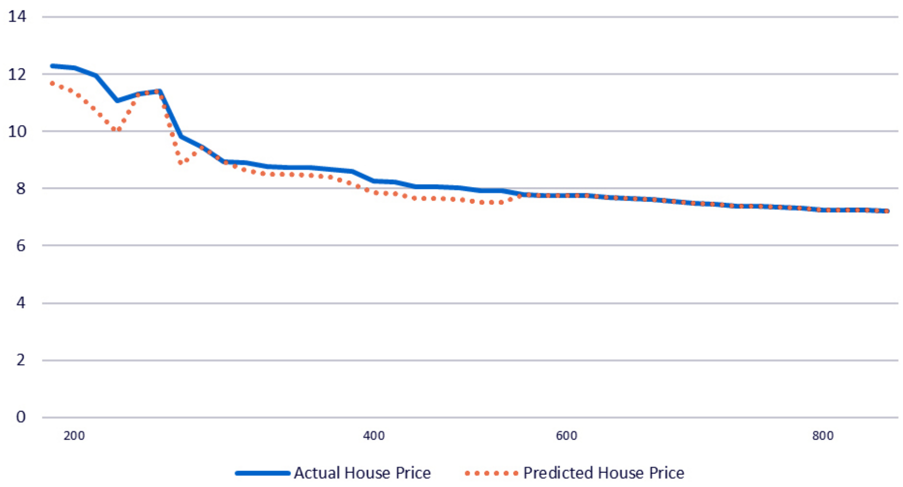

Figure 3. Comparison between theoretical and actual house price curve influenced by single factor (Jingmei MRT station, Taipei)

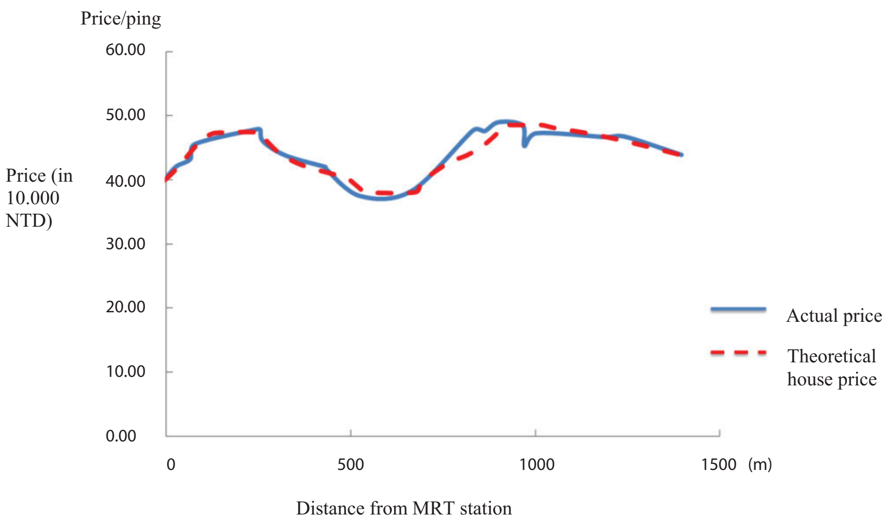

Figure 4. Comparison between theoretical and actual house price curve influenced by multiple factors (2 factors)

Table 4. Actual distance and case prices affected by multiple impact factors (3 factors)

Observation (59 in total)	Shortest distance to the closest MRT (m)	Longest distance to the farthest MRT (m)	Actual house price ($million NTD/m^2)	Predicted house price ($million NTD/m^2)
1 (Shortest distance)	62	907	14.62	14.62
52 (Longest distance)	751	1073	12.72	11.44
15 (Highest actual price)	211	847	15.76	14.97
20 (Highest predicted price)	321	866	15.75	15.75
57 (Lowest actual price)	368	745	10.40	10.40
6 (Lowest predicted price)	141	901	10.65	10.33
Average	391	818	13.10	12.92
Standard Deviation	202	245	1.31	1.37
Correlation coefficient r = 0.912				

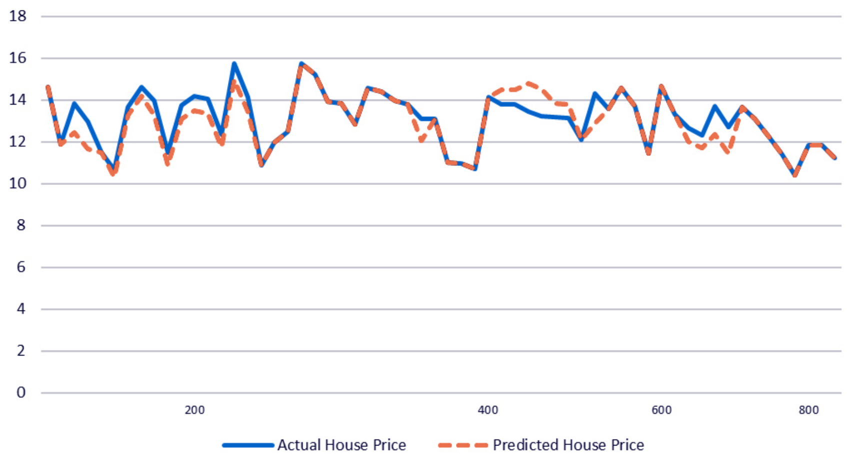

Figure 5. Comparison between theoretical and actual house price curve influenced by multiple factors (3 factors)

For example, if there are three MRT stations in the investigation area, 3^N types of function combination should be taken into consideration since each MRT station has a combination of three dynamic functions. As a result, for Case Study 4 with 3 attributes (3 MRT stations), the resulting correlation coefficient is r = 0.912 still highly matching to the real housing price as shown in Table 4 and Figure 5.

Figure 5 exhibits several peaks for the house price due to more attributes that can influence house price such as shopping malls, parks, stadiums, and schools. The dynamic impact function of surrounding multi-attributes for house pricing is then evaluated and ready for both further academic study and practical use.

Conclusions

This is an academic study focused on the construction of a dynamic impact function of surrounding multi-attributes for house pricing. This paper discusses not only real estate characteristics regarding distance effects but practical applications for improving appraisal accuracy. The analysis from the empirical implementation is carried out in order to test its impact on real estate pricing, to examine the real estate impact curve interpretation ability, and finally to apply the results to verify accuracy for the function. The implementation using empirical data is one of the contributions demonstrating the feasibility of the proposed function. In addition, the function is verified by empirical cases and the results can enhance appraisal accuracy, real estate market development, and strategies in the future. From the findings of correlation coefficient r = 0.944 and 0.946 for a single and multi-attributes, respectively, we can convey that the proposed function is an effective method to express (1) the ripple effects by multi-attributes to the target house price, (2) a dynamic distance pattern to the house price. It, thus, gives appraisers an accurate model for estimating house prices. This study differs from the previous studies in that the relationship between the proximity to the facility and the real estate price is presented in the form of a mathematical function with high accuracy. A thorough understanding of real estate appraisal and related knowledge can help across the field. As a result, the implementation of the proposed model can be used to establish different variables such as distance factors and proximity to "YIMBY" facilities in the field of selected location.

The findings explain real estate price well in a mathematical way based on distance; however, the model may be not applicable when other factors are out of current consideration or assumptions such as economic impact, political impact, force majeure, and long-run period. For example, economic status may be changed dramatically in a developing country. Political or unforeseen impact may create temporarily deviation in the investigated region. Any period longer than one year may also cause price escalation/de-escalation due to inflation/disinflation. The follow-up study is encouraged to deal with time integrated with macroeconomic issues that may lead practitioners to a different level of dynamic prediction model for real estate pricing.

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