Review of Issues in the Conventional Hedonic Property Pricing Model

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Abstract

The hedonic pricing model is extensively applied in property pricing modelling. It considers property as a bundled commodity and models its price as a function of its constituent parts – physical characteristics, neighbourhood attributes, and location factor. However, several issues in the conventional HPM hinder its accuracy in predicting property prices. This paper reviewed these issues with the ways of addressing them simultaneously. The review found the major issues in HPM include – normality of property prices, linearity, heteroskedasticity, multicollinearity, spatial dependence, spatial heterogeneity, spatial autocorrelation, and aggregation bias. These issues were found to substantially reduced the accuracy of property price modelling. These issues are minimised by specifying correct functional form which log-log specification was mostly found to be more efficient, dimension reduction using PCA or factor analysis, and property market segmentation. The use of these measures significantly reduces estimation errors and improves model fit thereby increasing the accuracy of property price prediction. The review recommends caution in choosing the correct functional form a well as the application of property market segmentation in modelling property market using different methodologies.

Keywords
Hedonic pricing model, heteroskedasticity, spatial dependence, autocorrelation, aggregation bias

1. Introduction

Real estate properties are strategic to the economic development of nations. They play a vital role in providing employment opportunities, the market for construction material, account for substantial household and institutional wealth, and contribute significantly to the Gross Domestic Product (GDP) of nations (Usman & Lizam, 2020; Usman, Lizam, & Adekunle, 2020; Joseph Awoamim Yacim & Boshoff, 2020). As such, significant attention is given to it by various stakeholders such as property investors, policymakers, financial institutions, households and academia. Most of the concern is the accurate pricing of real estate property assets. Property price is required for various purposes such as sales, purchase, taxation, mortgages, leasing, insurance, litigations, compensation, inheritance, balance sheet, inheritance, and investment and financing decision making (Núñez-tabales, Rey-carmona, & Caridad y Ocerin, 2016; Pagourtzi, Assimakopoulos, Hatzichhristos, & French, 2003; Usman, Lizam, & Burhan, 2020). These uses of property worth require accurate estimation of the property prices to be effective. Properties values are conventionally determined using the traditional income, cost and market approaches of valuation. It is noteworthy to distinguish between property price and value and how they relate in the context of property pricing.

Value is an estimated amount which the property is expected to exchange between a willing buyer and seller in perfect market condition. Royal Institution of Chartered Surveyors (RICS) adopted the definition of International Valuation Standard Council (IVSC, 2007) who defined property value as "the estimated amount for which a property should exchange on the date of valuation between a willing buyer and a willing seller in an arms-length transaction after proper marketing wherein the parties had each acted knowledgeably, prudently and without compulsion". Price, on the other hand, is the amount a property is exchanged between the seller and the buyer. Due to the imperfect nature of the property market, property price may not always be the true reflection of its market value partly because of information asymmetry or the seller or buyer's behaviour (Ogunba, 2013). Thus, the essence of property valuation is to estimate the property prices.

Properties are priced using various valuation methods. Conventionally, properties are valued using the income approach, the market approach and the cost approach. These three approaches comprise five methods used in traditional valuation – the investment, depreciated replacement cost, direct market comparison, residual, and profit methods of valuation (Aliyu, Sani, Usman, & Muhammad, 2018; Pagourtzi et al., 2003). The investment method of valuation traditionally uses term and reversion, layer and hardcore and equivalent yield method to estimate property price. However, the techniques were criticised and contemporary valuation models – Marshall's equated yield (discounted cash flow), Sykes Rational Model, and Crosby's hybrid Real Value model – were developed (Baum et al., 2006; Crosby, 1997; Effiong, 2015; Ogunba, 2007; Ogunba, 2013). The depreciated replacement cost method, the residual method, and the profit methods of valuation are mostly used for estimating prices of special properties that hardly change hand, a site with development or redevelopment potentials, and special income-producing properties such as hotels and filling stations. The use of these methods is therefore narrow. The direct market comparison method overcomes these limitations provided there is adequate comparable information.

The market comparison pricing approach compares the properties inherent and external characteristics with other comparable property transaction in the neighbourhood. The method adjusts for the subject property price based on actual property transaction information. Thus, its estimate is the closest to property price as it accounts for the market sentiment at the time and neighbourhood. The major limitation of the method is its reliance on the availability of sufficient property transaction information to make the comparison with. Where there are sufficient property transaction records, the analysis of the heterogeneous property attributes is difficult, time-consuming, costly, and inefficient when a larger number of property prices are to be estimated (Abdullahi, Usman, & Ibrahim, 2018).

With the sophistication of technology, the need to determine the price of a large number of properties, the need for efficiency in price determination, and with supporting theoretical basis, property price modelling are developed and continuously used in property pricing (Abidoye & Chan, 2017; Ahmad, Daud, & Esha, 2014; Gnagey & Tans, 2018; Gröbel & Thomschke, 2018; Raposo & Evangelista, 2017; Stamou, Mimis, & Rovolis, 2017). Such price modelling is based on a hedonic function which modelled property price as the function of the property's composite characteristics. The advantage of the method is that it uses past transaction records to predict the price of the subject property. Unlike the other method, the Hedonic Pricing Model (HPM) have the capacity to determine the implicit price of individual property characteristics, the buyers' willingness to pay for a property attribute, the relative importance of the attributes in the pricing, and can account for the influence of both positive and negative externalities on the property price (Bialkowski, Titman, & Twite, 2019; Costa, Fuerst, & Mendes-da-Silva, 2018; Kauko, 2003; Lee, 2009; Mayer, Bourassa, Hoesli, & Scognamiglio, 2019; Mora-Garcia et al., 2019; Stamou et al., 2017). However, certain issues limit the effectiveness of the hedonic pricing model in accurately determining property prices. Thus, this paper reviewed the issues that limit the performance of HPM in accurately predicting property prices. The rest of the paper is structured as followed. Section 2 present information of HPM, section 3 reviewed the issues in the hedonic pricing model, and section 4 for concludes.

2. Hedonic Pricing Model

The hedonic price modelling is advanced property pricing techniques used for property price estimation and prediction, construction of property price index, estimation of the implicit price of property attribute, measuring the willingness to pay for property services, and determining the impact of particular property characteristics as well as price premium and discounts associated with positive and negative property externalities respectively (Abidoye & Chan, 2017; Diewert & Shimizu, 2017; Evangelista, Ramalho, & Andrade, 2019; Francke & van de Minne, 2018).

The hedonic pricing model has been applied to various fields besides the real estate such as automobile and computer industry (Francke & van de Minne, 2018). In real estate, hedonic price modelling has been applied in valuing residential properties (Gnagey & Tans, 2018; Keskin, 2008, 2010; Stamou et al., 2017), commercial properties (Costa et al., 2018; Das, Smith, & Gallimore, 2017; Raposo & Evangelista, 2017), land prices (Fitzgerald, Hansen, Mcintosh, & Slade, 2019; Maddison, 2009), property economic depreciation (Diewert & Fox, 2015; Fisher, Smith, Stern, & Webb, 2005), and accounting for the impact of positive and negative externality on property values (Evangelista et al., 2019; Fell & Kousky, 2015; Jackson & Yost-Bremm, 2018; Mohammad, Graham, & Melo, 2017; Seo, 2016; Taylor, Phaneuf, & Liu, 2016; Zhong & Li, 2016).

The hedonic pricing model is a revealed-preference model that explain property prices based on their attributes (Yang, Wang, Zhou, & Wang, 2018). In the hedonic model, the property is considered as a composite good which is made up of its components. Thus the property price is the function of its characteristics which are priced simultaneously. Property is a heterogeneous good with bundled characteristics. The hedonic price modelled the implicit (shadow) prices of these bundle characteristics such that inferences can be made regarding their relative contribution to the property prices (Yu & Levy, 2017). The implicit price also indicated the amount a consumer is willing to pay (willingness to pay) for each property characteristics (Yang et al., 2018; Yu, Pang, & Zhang, 2017).

According to Seo, Salon, Shilling, & Kuby (2018), Hedonic price model is used to estimate the "economic value of nonmarket goods" by disaggregating the price of the good into the prices of its constituent characteristics, including the "non-market" features. When applied to real estate, the hedonic price model disaggregates the property price into the prices of the property's distinct characteristics known as implicit prices. The distinct property characteristics that make up the property are its physical characteristics, the neighbourhood characteristics and locational characteristics (Andres & Calvo, 2017; Dai, Bai, & Xu, 2016; Das et al., 2017; Deng, Ma, & Nelson, 2016; Gnagey & Tans, 2018; Liou, Yang, Chen, & Hsieh, 2016; Mohammad et al., 2017; Sevtsuk & Kalvo, 2018). The hedonic price thus takes the following form as expressed in equation 1.

$$P = f(S, N, L) \tag{1}$$

Where,
P = Property price
S = Structural (physical) characteristics
N = Neighbourhood characteristics
L = Locational characteristics

The general equation expressed property price as the function of the property physical (structural) characteristics, neighbourhood characteristics, and locational characteristics. This hedonic relationship is estimated using different methods such as Ordinary Least Squares (OLS) regression, the Artificial Neural Network (ANN), spatial econometric models, and others. The conventional hedonic pricing model using OLS is the most commonly used method for estimating property prices, determining shadow prices of individual property characteristics and constructing property price index (Abdullahi et al., 2018; Abidoye & Chan, 2017; Gnagey & Tans, 2018). Estimating the hedonic price model requires the selection of appropriate functional form that better model the relationship between property price and the property's characteristics variables. These functional forms are the linear, semi-log, double-log and Box-Cox linear. However, there is no general economic theory guideline on how to choose a particular functional transformation form, but the linear, semi-log, double-log and Box-Cox linear were reported to perform well in respective scenarios (Dziauddin, Powe, & Alvanides, 2014). The linear functional form is least preferred because the "assumption of constant marginal implicit prices are not tenable in most, if not all, cases" (Yang et al., 2018).

After specifying the functional form, accounting for unobserved heterogeneity is paramount. This is because the property market is highly heterogeneous (Gokmenoglu & Hesami, 2019) which can be controlled to improve the prediction accuracy. Other issues in hedonic price estimation are that of omitted and compounding variables. The compounding variables could lead to collinearity of the independent variables which leads to potential inconsistent and biased estimates of property prices (Mohammad et al., 2017). The issues are further review in the following section.

3. Issues in conventional HPM

The traditional hedonic price modelling has been used extensively in property market research. The model has been used to estimate residential property prices as well as commercial property prices. According to Francke & van de Minne (2018), the hedonic price model is more robust in residential property price estimation than commercial properties due to their heterogeneous nature, diverse drivers, and relatively lower level of transactions and turnover with the possibility of omitted variables in the data set.

Similarly, the conventional hedonic model may encounter potential biases due to inconsistency in the model, model misspecification errors due to omitted relevant variables, the use of incorrect functional form, inconsistency in measurement, and specification of the stochastic error term (Andres & Calvo, 2017). The major issues in the conventional hedonic model are the linearity issues, the collinearity, spatial autocorrelation, dependence and heterogeneity, and aggregation bias. These issues are likely to affect the accuracy of the property price estimation. The issues are discussed in the following subsections.

3.1 Normality, linearity and heteroskedasticity

The conventional regression analysis assumes a constant variance of the error term (homoscedasticity), normal distribution and linear relationships between the dependent variable and the independent variables. Linearity is the degree of relationship between the dependent variable and the independent variables such that the regression coefficient is constant across the range of values of for the independent variables (Hair Jr., Black, Babin & Anderson, 2010). Homoscedasticty refers to the presence of equal variance. The absence of equal variance of the residuals is known as heteroscedasticity. However, the relationship between property price and the predictive variables are mostly not always normally distributed, linear, or homoscedastic (Mccluskey, Mccord, Davis, Haran, & Mcilhatton, 2013). The violation of these assumptions among property pricing variables leads to prediction errors in property price estimation (Joseph A. Yacim & Bashoff, 2015). The property market is heterogeneous and may exhibit multiple equilibria (Dale-Johnson, 1982) with distinct submarkets such that estimating an equation of the whole market may violate the constant-coefficient assumption of the regression method.

To overcome the linearity issue in property price estimation, other functional forms other than the linear form are used. These functional forms include the semi-log functional form, log-log functional form, and the Box-cox functional form (Yang et al., 2018). However, due to the lack of theoretical backing for the selection of more appropriate functional form in property pricing modelling, the validity of the specified model may be challenged. Similarly, property market segmentation is also used to delineate the market into submarket such that each submarket is homogenous within. The property market segmentation is shown to significantly reduced the issue of linearity and heteroskedasticity and improves the accuracy of property price predictions (Usman & Lizam, 2020; Usman, Lizam, & Adekunle, 2020).

3.2 Multicollinearity

Collinearity is the degree or extent to which variables are correlated. Multicollinearity refers to the degree to which the independent variables are related and correlated. The regression analysis requires the independent variable to be unique and distinct from each other. The presence of multicollinearity reduces the predictive capacity of the added independent variable by the extent to which it is related to other independent variables such that as the correlation increases the unique variance and shared variance of the independent variable reduces and increase respectively (Hair Jr. et al. 2010).

Property has many features that are closely related and have the tendency of having greater correlation. The presence of high correlation among the property attributes causes possible estimation errors that violate the assumption of regression analysis (Abdullahi et al., 2018; Manganelli et al., 2014; Yu & Levy, 2017). Since most property price predictors are multicollinear, the property price estimation with accurate and stable coefficient is tedious (Dziauddin et al., 2014). Thus the collinearity issue is treated by observing the correlation among variable which are recommended not to exceed 0.85 (Awang, 2014), Variance Inflation Factor (VIF) recommended to be less than 10, and tolerance level recommended to be above 0.1 (Dziauddin et al., 2014; Pallant, 2011). One of the ways of dealing with collinearity issue is through dimension reduction using Principal Component Analysis (PCA) or Factor Analysis (FA). The PCA reduced the variables into set orthogonal factors. The resultant factors are mostly distinct from one another and do not pose a collinearity problem (Mooi, Sarstedt, & Mooi-Reci, 2018). For instance, property attributes can be reduced into a set of distinct factors which are subsequently used for the hedonic analysis (Bourassa, Hoesli, & Macgregor, 1997; Chao Wu, Ye, Ren, & Du, 2018).

3.3 Spatial dependence, heterogeneity and autocorrelation

The hedonic price model estimates the property price based on its physical characteristics, neighbourhood attributes and locational characteristics. Although properties have distinct characteristics, they share a similar neighbourhood and relative location with one another. Properties that are located closer together are likely to be more related than with distant properties (Liang, Reed, & Crabb, 2017). According to Tobler (1970), "everything is related to everything else, but nearer things are more related than distant things". This applies to the property market such that neighbouring properties are more related than distance things and mostly share price similarities. The existence of correlation among nearby property is regarded as spatial autocorrelation. In other words, spatial autocorrelation occurs when a "variable measured at a certain location is spatially correlated with the same variable located nearby (Dziauddin et al., 2014).

Thus spatial dependence occurs when the price of a particular property is spatially correlated with the price of nearby properties. Spatial dependencies occur because nearby properties mostly share a common neighbourhood and locational attribute and similar characteristics in certain areas (Francke & van de Minne, 2018). Similarly, Yu, Pang, et al. (2017) submitted that spatial dependence is found in the property market because "property values can be influenced by adjacent properties. Property values can also be influenced by attributes from neighbouring properties or omitted variables which are spatially correlated".

Spatial dependence caused by spatial autocorrelation is the correlation of price due location similarity such that similar and dissimilar prices of given property characteristics tend to cluster in space signifying positive and negative autocorrelations respectively (Feng & Humphreys, 2008). In addition to the neighbourhood and location effect, the spill-over effect of adjacent property prices may lead to property prices to be spatially dependent. The neighbourhood effect and the spill-over effect are classified as reaction effects and interaction effect. The reaction effects deal with the property prices response to underlying common factors interaction effect deal with how the property prices affect one another (Feng & Humphreys, 2008).

Spatially heterogeneity, on the other hand, refers to a situation where the relationship between property price and its attribute vary spatially. This occurs when regression parameter estimates for the property attributes vary over a geographical area (Dziauddin et al., 2014). The presence of spatial dependence (autocorrelation) and heterogeneity poses a serious problem to the hedonic property price prediction. With the presence of spatial dependence and spatial autocorrelation in the error term in the hedonic model leads to inefficient, biased, and inconsistent parameter estimates (Feng & Humphreys, 2008; Liang et al., 2017; Seo, Salon, Kuby, & Golub, 2018; Xu et al., 2016; Yang et al., 2018; Yu, Pang, et al., 2017).

The conventional hedonic model attempt to account for autocorrelation in property pricing by controlling for spatial effects through increasing sample size, controlling the market, and property market segmentation (Dziauddin et al., 2014). Although these methods improve the accuracy of the price estimations, the influence of spatial dependence on the property prices is not adequately accounted for. Various studies using spatial analysis techniques found the presence of significant spatial dependence and heterogeneity in property market pricing (Fotheringham & Park, 2017; Ke et al., 2017; Sevtsuk & Kalvo, 2018). Thus, the traditional hedonic modelling is relatively deficient in accounting for the effect of spatial dependence and heterogeneity on property pricing.

3.4 Aggregation bias

As severally noted, properties are as heterogeneous as its market is (Tian, Peng, Wen, Yue, & Fang, 2020; Usman, Lizam, & Adekunle, 2020). The property price estimation was shown to exhibit so many issues that tend to affect the accuracy of the prediction. These were issues of data normality, non-linear relationship between property attributes and price, heteroskedasticity, spatial heterogeneity, and spatial autocorrelation and dependence (Abdullahi et al., 2018; Dziauddin et al., 2014; Fell & Kousky, 2015; Xu et al., 2016; Joseph A. Yacim & Bashoff, 2015). The presence of these issues in price estimation violates the assumption of constant and equal variance and therefore renders the equilibrium and constant implicit price assumption of the hedonic price theory not fully achievable. Since properties exhibit heterogeneity across space and attributes, estimating the hedonic price across these heterogeneous boundary leads to the problem of aggregation biases which may jeopardise the parameter estimates and render them inconsistent, inefficient, and inaccurate (Chen, Cho, Poudyal, & Roberts, 2009; Dziauddin et al., 2014; Goodman & Thibodeau, 2003; Inoue, Ishiyama, & Sugiura, 2018; Kauko, Hooimeijer, & Hakfoort, 2002; Lim, Yoo, Park, Pacific, & Korea, 2018; Mayer et al., 2019; Xu et al., 2016). The problem of aggregation bias is minimised through property market segmentation (Gabrielli, Giuffrida, & Trovato, 2017; Keskin, 2008; Tu, Sun, & Yu, 2007; Warren, Elliott, & Staines, 2017).

Market segmentation is the delineation or disaggregation of the property market into uniquely distinct submarkets which are homogeneous within, and heterogeneous among, the submarkets. Several studies have shown that market segmentation improves the accuracy of property price prediction significantly (Baroni & Baroni, 2016; Baudry & Maslianskaia-pautrel, 2015; S. C. Bourassa, Cantoni, & Hoesli, 2007; Goodman & Thibodeau, 2003; Manganelli et al., 2014; Pryce, 2013; Shi, Guan, Zurada, & Levitan, 2015). Although there are several methods of property market segmentation, conventionally, separate hedonic equations are estimated for each distinct submarket derived either a priori or through data-driven methodologies (Bangura & Lee, 2020; Inoue, Ishiyama, & Sugiura, 2020; Rosmera & Lizam, 2016; Usman, Lizam, & Adekunle, 2020; Y. Wu, Wei, & Li, 2020). Disaggregating the models into submarket models is shown to reduce the weighted standard error and in most cases improve model fit thereby increasing the models' prediction accuracy (Bourassa, Hoesli, & Peng, 2003; Bourassa et al., 1997; Changshan Wu & Sharma, 2012; Wu et al., 2018).

4. Conclusion

The strategic importance of property to individuals, households, institutions, governments, and the economy are noted in the literature such that various stakeholders attached prominence to its pricing. The aim of any price prediction is improved accuracy. Property prices are determined traditional using the five conventional methods of valuation – the market comparison method, the investment method, the replacement cost method, the residual method and the profit method. The contemporary methods include the discounted cash flow method, the hard-core and layer method, Marshall's equated yield (discounted cash flow), Sykes Rational Model, and Crosby's hybrid Real Value model. These models have their respective strengthens and weaknesses.

With sophistication in technology, the need to appraise many properties, and minimise time and cost of the appraisal, property price modelling is developed. The most commonly used method is the hedonic pricing model which models property price as the function of its physical characteristics, neighbourhood attributes and location factor. However, the hedonic pricing model has some issues that limit its accuracy. This paper reviewed the issues in the hedonic pricing model that affect the accuracy of property prices. The review found the major issues in HPM include – normality of property prices, linearity, heteroskedasticity, multicollinearity, spatial dependence, spatial heterogeneity, spatial autocorrelation, and aggregation bias. These issues are minimised by specifying correct function form which log-log specification was mostly found to be more efficient, dimension reduction using PCA or factor analysis, and property market segmentation. The paper, therefore, recommends caution in choosing correction functional form and the application of property market segmentation in modelling property market.

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