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CONVENTIONAL METHODS IN HOUSING MARKET ANALYSIS: A REVIEW OF LITERATURE

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Abstract. Housing market analysis has witnessed considerable changes in recent decades, especially as a result of the complexity of human settlements and the dynamics of property market analytical techniques. This paper reviews various techniques/methods adopted by researchers and housing experts in analysing the housing market in recent times. The present study is a literature review and, therefore, essentially relies on published data sourced from academic journals, conference papers, thesis, and other secondary sources. The paper highlights the methods considered appropriate and relevant for different property market scenarios, especially in developing countries. The paper, therefore, recommends what it regards as the most appropriate basis for a housing market analysis and research in developing countries against the backdrop of the dynamics of the property market.

Keywords: *Conventional methods, Housing market, Literature, Scenarios, Techniques.*

INTRODUCTION

The housing market is very imperative because of the place it holds in the economy (Seo, 2008). Housing construction easily contributes to the Gross Domestic Product (GDP) and its market has a direct impact on the national and international economy (Hu, Cheng, Wang, & Xu, 2013). Consequently, immovable characteristics of housing (Renigier-Biłozor, Biłozor, & Wisniewski, 2017), its location (Cichociński & Dąbrowski, 2013), its importance in the broader economy (Hill & Scholz, 2017), the growing urban population coupled with rising problems of adequate and affordable housing and complex human settlement (UN-Habitat, 2011) and several factors that determine housing price (Mohammed & Sulyman, 2019a) necessitate different approaches to a housing market analysis.

Scholars have adopted and developed several conventional methods for the housing market analysis (Mohammed & Sulyman, 2019a). These methods include: hedonic model (Yusuf & Resosudarmo, 2009), logit model (Brounen & Kok, 2011), matched pair audits method (Hanson & Hawley, 2011), spatial approach (Mohammed & Sulyman, 2019b), space syntax (Xiao, 2012), dynamic general equilibrium model (X. Li & Tang, 2018), agent-based model (Ge, 2017), analytical hierarchy process (Tupenaite, Kanapeckiene, & Naimaviciene, 2017), multiple regression model (Wickramaarachchi, 2016), local projection method (Cameron, 2018), ordinary least squares (Zhang & Zhao, 2018), cluster analysis (Guan & Gao,

2018), month-based model (Bérard & Trannoy, 2018), Mahalanobis-metric matching model (Jung & Yoon, 2018) and artificial neural network model (Del Giudice, De Paola, & Forte, 2017).

However, few among these methods are widely used in the literature of the housing market. Some of these methods are modifications of other models, while some are independent. These methods are frequently adopted by scholars in the housing market analysis. These are: multiple regression model, hedonic model, spatial approach, artificial neural network model, and mixed methods.

It is therefore imperative to review these methods of housing market analysis. The goal of the study is to review the empirical literature on methods in the housing market analysis in order to examine the best methods for different scenarios.

1. METHODOLOGY

The study adopted an archival research methodology where the focus of the research was on a review of empirical studies on the conventional methods in the property market analysis. Thus, the required data for the study were based on secondary sources obtained from academic journals, conference papers, and thesis from both printed and online sources. Studies with clear methodologies were selected. The process is presented in Fig. 1.

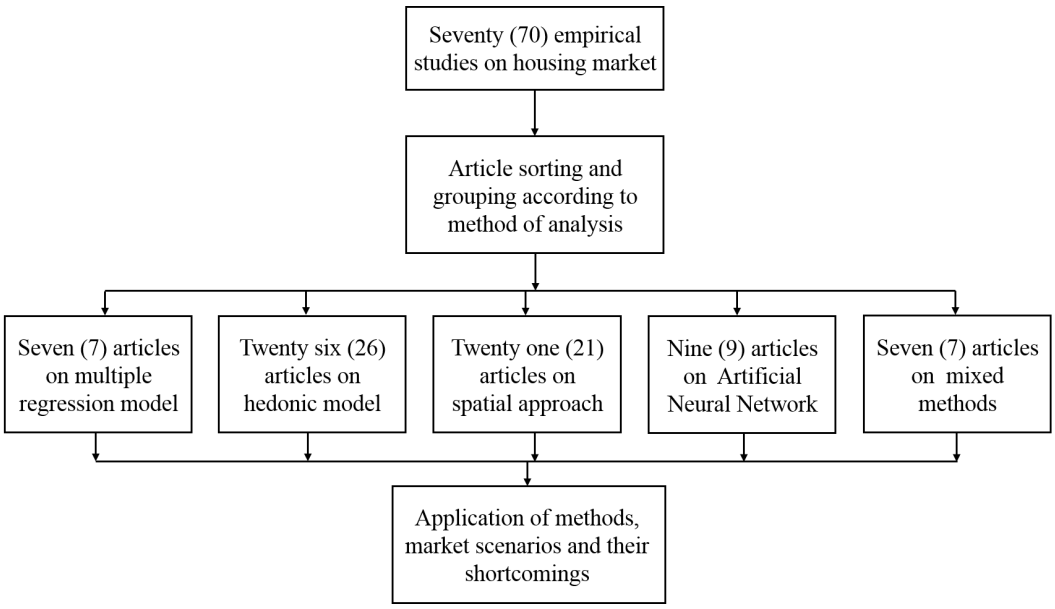

Fig. 1. Methodology and Review Process.

2. FINDINGS

Multiple Regression Model

Many studies have been conducted adopting multiple regression to analyse the housing market. For example, a study by Ajayi *et al*. (2015) adopted the multiple

regression model to analyse the relationship between infrastructural facilities and rental value where the findings of their study showed that there was a strong impact of water facilities on rental value.

Abdullahi *et al*. (2018) adopted the multiple regression analysis in mass appraisal of house price estimation in Kaduna North, Nigeria. The house prices were considered based on the two basic micro determinants: structural attributes and location of houses. Their study found that variables that were significant in determining house prices in Kaduna included the type of house, availability of security post, years of the transaction, and the type of door, availability of swimming pool, as well as location of the houses. However, their study considered the number of bedrooms, condition of the house, type of ceiling, and number of living rooms as not significant in influencing house prices. A mass appraisal model was developed for Kaduna North using the significant variables. Part of their recommendation was that in the future, the mass appraisal of residential properties in Kaduna North could be carried out using this model to achieve objectivity, efficiency, fairness and improve the accuracy of the property taxation system, which would improve government revenue generation, and encourage the development of physical infrastructure in Kaduna North.

In a study by Antoniucci & Marella (2017), the multiple regression model was adopted to analyse variation in housing market polarization in Italian cities since 2008, where it was found out that housing market polarization had a significant correlation with urban density, socioeconomic characteristics, and housing affordability. Wickramaarachchi (2016) used a multiple regression model to develop an index that would provide a guideline in determining rental value in the housing market. Oluwadamilola (2017) also used multiple regression to examine the influence of socioeconomic factors on the rental value of accommodation. Similarly, Huang, Li & Ning (2018) used the regression model to assess the effect of economic policy uncertainty on China's housing market.

The adoption of the multiple regression model in the housing market analysis has been criticised by many authors (Xiao, 2012). This criticisms has brought about the modification among which is the hedonic model.

Hedonic Model

The hedonic approach is one of the most used conventional approaches to the housing market analysis (Sopranzetti, 2015). Using the hedonic approach, expenditures on housing can be decomposed into measurable prices and quantities, so that rents for different dwellings or identical dwellings in different places can be predicted and compared (Malpezzi, 2002; Meese & Wallace, 1991; Sopranzetti, 2015). This approach has been adopted by several authors in analysing the housing market (Abdullahi et al., 2018; Anselin & Le Gallo, 2006; Goodman & Thibodeau, 1995; Helbich, Brunauer, Vaz, & Nijkamp, 2014; Liao & Wang, 2012; Lu, 2018; Oladunni, Sharma, & Tiwang, 2017; Sandmo, 2014).

For example, Lu (2018) examined the relationship between the view orientation of an apartment and its property value in the context of the Shanghai housing market. The author used a hedonic pricing model and a unique dataset, comprised

of apartment attributes, ambient environmental indicators, and urban spatial structure, which showed that a south-facing orientation was associated on average with a 14 % premium in the property value.

Liao & Wang (2012) applied the hedonic approach where they made use of publicly accessible sources to construct a new micro-dataset for an emerging Chinese city, Changsha, and it incorporated quantile regression with spatial econometric modelling to examine how implicit prices of housing characteristics might vary across the conditional distribution of house prices. Razali *et al*. (2018) examined the property market price response to flood hazard in the Langat River flood area in the State of Selangor, Malaysia. They suggested that environmental attributes were very subjective and relatively new in the valuation theory. Cajias, Fuerst & Bienert (2019) assessed the energy efficiency levels of the housing stock, which was of particular concern in the private rental market where capital costs and utility cost savings were not shared in equal measure by landlords and tenants. Liebelt, Bartke & Schwarz (2018) analysed the influence of Urban Green Spaces (UGS) on residential property prices in Leipzig, Germany, by applying a hedonic pricing analysis. Yusuf & Resosudarmo (2009) in their study adopted the hedonic model to analyse Jakarta housing market considering air pollution effects on a rental value. Bin *et al*. (2008) used the hedonic model to examine the effect of flood hazards on coastal property values. Wu, Deng & Liu (2014) constructed a house price index in the Nascent housing market using the hedonic model. The hedonic model was also used by Muehlenbachs, Spiller & Timmins (2015) in assessing the housing market impact of shale gas development. Wu *et al*. (2017) found out that the effect of parks on the housing price was statistically significant using the hedonic model. Gambo (2012) analysed the influence of violent ethnoreligious conflict on residential property values using the hedonic model. By means of the hedonic model, critical factors determining housing prices were assessed by Adegoke (2014).

Chen & Li (2017) analysed the cumulative impact of polluted urban streams on property values using the hedonic model. Other scholars who used the hedonic model: Kim, Lee, Lee and Choi (2019) in examining the local impact of urban park plans and park typology on the housing price; Kemiki, Ojetunde & Ayoola (2014) used it to analyse noise and dust impact of a cement factory on house prices; Devaux, Berthold & Dubé (2018) assessed the economic impact of a heritage policy on residential values; Gulyani *et al*. (2018) also used the hedonic model to analyse demand and living conditions in the urban housing market.

The model has been widely accepted in housing market literature mostly by real estate experts and urban planners. However, the method is not free from criticism.

Spatial Approach

One reason house prices may be spatially autocorrelated is that property values in the same neighbourhood capitalize on shared location amenities. Location characteristics that influence house prices include neighbourhood characteristics, accessibility, and proximity externalities (Basu & Thibodeau, 1998). The spatial

approach has been adopted by several authors in analysing the housing market (Basu & Thibodeau, 1998; Delbari, Afrasiab, & Jahani, 2013; Diao, 2015; Dubin, 1998; Dubin, 1992; McCluskey, Deddis, Lamont, & Borst, 2000; Moral, 2008; Tu, Sun, & Yu, 2007; Wang et al., 2017; Chao Wu, Ye, Du, & Luo, 2017; Zhang, Sun, & Stengos, 2018).

For example, Zhang & Tang (2016) analysed spatial patterns of housing prices in Chinese cities with an emphasis on public attention. They argued that unavailability or ill-documented detailed housing price data posed a serious challenge for the housing price assessment in China. They also argued that web search engine records of individual search activities and the analysis of these data in cyber-space might provide an insight into understanding of public attention and how it was associated with real geographic space. Through the analysis of the web query activities based on the Baidu Index, spatial patterns of public attention on housing prices were explored. In achieving this objective, a new index based on keyword query outcomes was proposed, where spatially heterogeneous patterns of housing price attention were analysed using the Baidu search database with a focus on 19 Chinese cities, including large and medium-sized cities. The spatial network structure of housing price attention was evaluated and a new index was developed to measure the extent of interaction relationships among the studied cities. The results of the evaluation of the spatial interaction of housing price attention among the cities in the new method were consistent with those from a gravity model. The Baidu Index-based indicators showed strong spatial relationship patterns among the cities, which formed urban agglomerations. Their results further demonstrated that the web search engine approach, combining both cyber-space and geographic space, provided a basis for the assessment of the housing price attention and its spatially explicit patterns in China.

Kuntz & Helbich (2014) compared the accuracy of the prediction of univariate kriging variants, namely universal kriging (UK) and detrended kriging (DK), and multivariate extensions, including universal cokriging (UCK) and detrended cokriging (DCK). Both later techniques consider neighbourhood and structural characteristics as auxiliary variables. While the UK and DK price surfaces showed nearly identical cross-validated accuracies, the cross-validation-based prediction accuracy of DCK and UCK differed in favour of the latter. They suggested that either UK or DK could be used by real estate agencies for a univariate sample of property prices, while UCK was recommended for a multivariate case, although numerically more complex.

Li, Ye, Lee, Gong, & Qin (2017) argued that there was fast-paced development in China's real estate industry in recent decades. However, there are spatial imbalances between urban economic growth and that in both rural and urban areas, excessive growth and house price fluctuations attracted public attention. They argued that the focus of urban and regional economic research had shifted to these issues. An efficient, reliable, and accurate housing price prediction remains much required and disputable issue. Consequently, several studies emerged due to the trends and changes in the financial market, urbanisation processes, and population migration, to examine the determinants of housing price fluctuations. They examined the spatiotemporal trends of the housing price fluctuation in the big data

context, where data from China's leading online real estate platform (sofang.com) were used. Spatial data analytics and modelling techniques were adopted to identify housing price spatial distribution at the micro-level, spatiotemporal dynamics of houses in the housing market, and assess the geographic disparity of housing prices. Their results revealed the spatiotemporal patterns of the housing prices in a large metropolitan area, demonstrating the importance of big data and how big data could be handled.

Helbich *et al*. (2014) investigated single-family houses by modelling spatial heterogeneity (SH). They argued that the capabilities of the global and locally weighted hedonic model were explored using single-family house prices in Australia. They suggested that even if SH model could not be fully conducted using regional indicators and that unmodeled SH required technical amendments, the results emphasised their importance in a reliable model. Since the SH is beyond the level of regional indicators, it brought about processing locally weighted regressions. For instance, limitations of fixed effects are prevented by mixed geographically weighted regression (MGWR) by exploring price effects that are both spatially stationary and non-stationary. Apart from prediction error reduction, they suggested that the misspecifications of the global model arose from improper selected fixed effects. They found out that regional indicators and purely local models could not be compared with SH implicit prices in terms of complexity.

Iliopoulou & Stratakis (2018) analysed housing prices in the Greater Athens region employing data for the structural and locational characteristics of dwellings. They used a sample from the total housing supply in 2017 and included several thousand dwellings for sale available by online real estate agencies. A description of the houses was provided in terms of their structural characteristics, such as the type of a dwelling, size, floor, number of bedrooms, parking, etc. Also, several characteristics relative to the location of dwellings, such as distance from the closest metro station or distance from the city center, were calculated in a GIS environment. Due to the spatial dependency of the residuals in the ordinary least squares method, a spatial regression model (geographically weighted regression) was also presented, which improved the accuracy of the prediction. They concluded that most locational characteristics did not contribute significantly to the explanatory power of a regression model when compared to structural characteristics.

Chen (2018) examined spatial differentiation of urban housing prices in Guangdong province in China and factors influencing housing prices. Spatial heterogeneity of housing prices and that of their impact factors were examined during the period of 1995–2015 using ESDA and GWR models. The study found out that a certain circle structure was shown in the spatial structure of housing prices in the region. While relatively high housing prices were found in the Pearl River Delta region, there was a high disparity between housing prices of Zhongshan, Huizhou, and other cities. The price of housing in the cities of northern, western and eastern Guangdong was low, which showed a significant high variation from the housing prices of cities in Pearl River Delta, also Shantou and its surroundings had a high difference between the housing prices.

Ajayi, Nuhu *et al*. (2015) analysed the relationship between housing conditions and rental value using a spatial approach. Spatial network analysis was adopted by

Xiao, Webster & Orford (2016) in assessing house price effects of changes in urban street configuration. Similarly, Mohammed and Sulyman (2019b) examined spatio-temporal dynamics of the housing market in Bida, Nigeria. This approach is widely used and not free from criticism but much adopted in the literature of the housing market by urban planners (Xiao, 2017). This model is more acceptable in the literature by urban planners and is a trend in real estate research.

Artificial Neural Network

Several studies have been performed on housing market using an artificial neural network (Coakley & Brown , 2000; Kauko, 2003; Kauko, Hooimeijer, & Hakfoort, 2002; Khalafallah, 2008; Li *et al*., 2014; Limsombunc *et al*., 2004; Moulton & Preece, 2002; Selim, 2009). For example, Kauko *et al*. (2002) assessed the housing market of Helsinki in Finland using neural network modelling. Their study showed how various dimensions of housing submarket formation were identified by exploring patterns in the dataset, and also revealed classification abilities of two neural network techniques: the Learning Vector Quantisation (LVQ) and Self-Organising Map (SOM). They argued that location and house type relatively determined housing submarket formation in Helsinki.

Selim (2009) examined the housing price determinants in Turkey using the Household Budget Survey data of the year 2004. He argued that one of the shortcomings of the hedonic method was that a locational value that was usually analysed on large data sets required formality based on the microeconomic theory. He also argued that an artificial neural network (ANN) was employed because there was potential non-linearity in the hedonic functions and that ANN was an alternative method. When comparing the prediction performance between the hedonic and ANN models, the study suggested that ANN could be a better alternative for housing price prediction in Turkey.

Limsombunc *et al*. (2004) performed an empirical study in Christchurch, New Zealand, comparing hedonic and ANN models on the housing price prediction. About 200 houses were randomly selected from the Harcourt website. Factors considered in the model included: house type, house age, house size, number of bathrooms, number of bedrooms, number of garages, neighbourhood amenities, and geographic location. The empirical result was argued to be in favour of ANN on house price predictions.

Khalafallah (2008) developed ANN-based models to support home developers and real estate investors in their critical tasks. He defined the decision variables, methodological design, and model implementation. Historical market performance data sets were utilised in the model to train the ANN to predict the future market performance. The model example was used to demonstrate the model capabilities in assessing and predicting the housing market performance. The model validation showed error in predictions in the range of between –2 % and +2 %.

Li, Zhang, Yang, & Wang (2014) applied an ANN to innovatively predict real estate development phases and identify its life cycles in China, using 1993–2008 historical training samples that were well-trained. Their results indicated that ANN performance had reached high accuracy due to the outcome of the oscillational

characteristics of China's housing market. They argued that volatility in China's real estate cycles became more glaring during 2008 due to deepening governmental interventions. But when the housing market reached its peak in 2009, recession quickly set in 2010, and then approached its trough in 2011. They concluded that several interventions by the governmental policies had tremendous impact on the housing market since 2008, particularly on the duration and frequency of the real estate cycles and expansion of the real estate business.

Del Giudice, De Paola & Forte (2017) argued that neural networks (NNs) had a wide interest due to empirical achievements in a wide range of learning issues. According to the authors, NNs are highly expressive models that can learn complex function approximations from input/output, with a particular ability to train them on massive data sets with stochastic optimization. They also argued that the Bayesian approach to NNs could potentially avoid some of the problems of stochastic optimisation and the use of Bayesian learning was well suited to the problem of real estate appraisals. Bayesian inference techniques are very interesting to deal with in a small and noisy sample in the field of probabilistic inference carried out with a neural model. For this purpose, they experimented on an NN model with Bayesian learning. The output distribution was calculated operating a numerical integration on the weight space with the help of the Markov Chain Hybrid Monte Carlo Method, which they concluded to be the best for the housing market analysis.

However, Kauko (2003) adopted a spatial approach to a neural network analysis. He worked on current neural network applications involving spatial modelling of property prices. He evaluated the pros and cons of neural network models of property valuation (particularly the 'self-organising map', SOM) in comparison with hedonic models, and provided some examples of the application of the SOM method. His particular interest was how different locational, environmental, and social factors affected housing market segments and house price levels. He argued that these objectives were conveniently handled with a method based on the SOM.

This model suffers setbacks in its application to the housing market by real estate surveyors and urban planners.

Mixed Methods

Housing market analytical methods are combined in the literature of the housing market to have robust results. These combinations are attributed to some shortcomings in the application of single methods or models. For example, a principal components analysis is usually combined with the regression model to reclassify factors that determine a rental value into groups of significance. Regression analysis and geographic field models are combined to analyse the effects of locational factors on the housing prices of residential communities. Zhao (2018) used a cross weight coefficient and regression models to analyse the relationship between a fertility rate and housing price. The month-based model and the hedonic model were combined by Bérard and Trannoy (2018) to assess the impact of the 2014 increase in real estate transfer taxes on the French housing market. Some other authors combined the hedonic model and spatial approach

techniques to analyse the housing market. For example, Chung, Seo & Kim (2018) combined the spatial approach and the hedonic model to analyse price determinants and GIS analysis of the housing market. The same combination was adopted by Cui, Gu, Shen & Feng (2018).

Paz & McGreal (2018) used the price index and the hedonic model to compare different results of housing price indices. Zhang & Zhao (2018) determined the informal housing price in Beijing using ordinary least squares and multi-level hedonic models. Principal component and lagged sentiment proxies were combined by Zhou (2018) to examine the interaction between housing market sentiment and government interventions. Latinopoulos (2018) examined the effect of sea view on room rates alongside other structural and locational attributes where GIS system was used to apply a spatial hedonic model. A semi-parametric geographically weighted regression model was used to assess the local effects, as well as to investigate the spatial variability of the selected attributes.

A combination of methods continues to be seen as the best approach in analysing a housing price by urban planners and real estate experts. However, an artificial neural network is given less attention in this regard.

3. DISCUSSION

The hedonic model is one of the most used methods/models in the housing market analysis (Mohammed & Sulyman, 2019a). Research from the developing world has proven that the hedonic model is widely used (Gambo, 2012; Malpezzi, 2002). The findings of this review proves that multiple regression models and hedonic models require combination with other methods such as a principal component analysis to enhance factors responsible for housing prices. For example, the house price index was constructed by Wu, Deng & Liu (2014), and Wickramaarachchi (2016) using the hedonic model and multiple regression model, respectively. Their models were exaggerated because they included those factors that were much less significant; this was because they could not reduce the factors to minimal significant factors. The findings of the review also prove that spatial analytical models in the housing market analysis have some shortcomings where in most cases the models are exaggerated most especially the spatial autocorrelation models (Xiao, 2012). The study shows that authors in developing countries applied the multiple regression model, hedonic model, and spatial analysis in analysing a housing price. For example, Abdullahi *et al*. (2018), Ajayi *et al*. (2015), and Oluwadamilola (2017) applied the multiple regression model in analysing the rental value of residential housing. For the hedonic model, Kemiki, Ojetunde & Ayoola (2014), Adegoke (2014), and Gambo (2012) analysed housing prices with it. Authors also adopted spatial analytical techniques for housing price analysis. For instance, Mohammed & Sulyman (2019b) adopted spatial autocorrelation to develop spatial and temporal housing price model. Spatial autocorrelation was also adopted in analysing residential rental values (Ajayi, Nuhu *et al.* 2015). Artificial neural network as a machine learning model has been adopted by many researchers of the housing market due to its high predictive ability and sorting of data into different layers based on their significance. It is said to be better than multiple

regression and hedonic models due to its predictive potential and performance, and a better alternative for prediction of house prices (Limsombunc *et al*., 2004; Selim, 2009). It also has capabilities in analysing and predicting housing market performance (Khalafallah, 2008). Artificial neural network is not free from criticism but can be better when combined with the spatial approach. Artificial neural network is given less preference in developing world literature of the housing market.

CONCLUSIONS

In conclusion, methods that are widely used in the literature of the housing market are the multiple regression model, hedonic model, spatial approach, artificial neural network model, and mixed methods. The hedonic model is one of the most used methods/models in the housing market analysis in the developing world. The adoption of the hedonic model is attributed to the shortcomings of the multiple regression model. Spatial analytical models in the housing market analysis used in housing market research also have some shortcomings where in most cases the models are exaggerated, most especially the spatial autocorrelation models. Artificial neural network is better than multiple regression and hedonic models due to its predictive potential and performance, and a better alternative for prediction of house prices. The model has a high predictive ability and can reclassify data without requiring other analytical methods. Spatial models would be better when combined with an artificial neural network. Artificial neural network is given less preference in the developing world literature of the housing market. It is therefore recommended to adopt the artificial neural network in the housing price analysis for better housing policy formulation in developing nations.

REFERENCES

Abdullahi, A., Usman, H., & Ibrahim, I. (2018). Determining House Price for Mass Appraisal Using Multiple Regression Analysis Modeling in Kaduna North, Nigeria. *ATBU Journal of Environmental Technology*, *11*(1), 26–40.

Adegoke, O. J. (2014). Critical factors determining rental value of residential property in Ibadan metropolis, Nigeria. *Property Management*, *32*(3), 224–240. https://doi.org/10.1108/PM-05-2013-0033

Ajayi, M. T. A., Kemiki, O. A., Mohammed, J. K., Adama, U. J., & Ayoola, A. B. (2015). A Study on the Application of GIS in the Assessment of the Impact of Infrastructure on Residential Property Value in Minna. P*resented at the 21st Pacific RIM Real Estate Society (PRRES) Conference*, Kuala Lumpur, Malaysia.

Ajayi, M. T. A., Nuhu, M. B., Bello, M. Z., Shuaib, S. I., Owoyele, G., Onuigbo, I., … Alias, A. (2015). A GIS Based Assessment of the Relationship between Housing Conditions and Rental Value in Government Built Housing Estates in Minna. *Journal of Building Performance*, *6*(1), 50–62.

Anselin, L., & Le Gallo, J. (2006). Interpolation of Air Quality Measures in Hedonic House Price Models: Spatial Aspects. *Spatial Economic Analysis*, *1*(1), 31–52. https://doi.org/10.1080/17421770600661337

Antoniucci, V., & Marella, G. (2017). Is social polarization related to urban density? Evidence from the Italian housing market. *Landscape and Urban Planning*. https://doi.org/10.1016/j.landurbplan.2017.08.012

Basu, S., & Thibodeau, T. G. (1998). Analysis of Spatial Autocorrelation in House Prices. *Journal of Real Estate Finance and Economics*, *17*(1), 61–85. https://doi.org/10.1023/A:1007703229507

Bérard, G., & Trannoy, A. (2018). The impact of the 2014 increase in the real estate transfer taxes on the French housing market. *Economie et Statistique / Economics and Statistics*, (500t), 179–200. https://doi.org/10.24187/ecostat.2018.500t.1951

Bin, O., Kruse, J. B., & Landry, C. E. (2008). Flood Hazards, Insurance Rates, and Amenities: Evidence From the Coastal Housing Market. *Journal of Risk & Insurance*, *75*(1), 63–82. https://doi.org/10.1111/j.1539-6975.2007.00248.x

Brounen, D., & Kok, N. (2011). On the economics of energy labels in the housing market. *Journal of Environmental Economics and Management*, *62*(2), 166–179. https://doi.org/10.1016/j.jeem.2010.11.006

Cajias, M., Fuerst, F., & Bienert, S. (2019). Tearing down the information barrier: The price impacts of energy efficiency ratings for buildings in the German rental market. *Energy Research & Social Science*, *47*, 177–191. https://doi.org/10.1016/j.erss.2018.08.014

Cameron, T. (2018). *The House Rules: Housing Market Responses to Oil Price Shocks in Canada* (Masters Dissertation). University of Ottawa, Ottawa, Canada.

Chen, F. (2018). Spatial Differentiation of Urban Housing Prices in Guangdong Province and Its Influencing Factors. *Modern Economy*, *09*(04), 664–681. https://doi.org/10.4236/me.2018.94043

Chen, W. Y., & Li, X. (2017). Cumulative impacts of polluted urban streams on property values: A 3-D spatial hedonic model at the micro-neighborhood level. *Landscape and Urban Planning*, *162*, 1–12. https://doi.org/10.1016/j.landurbplan.2017.01.012

Chung, Y., Seo, D., & Kim, J. (2018). Price Determinants and GIS Analysis of the Housing Market in Vietnam: The Cases of Ho Chi Minh City and Hanoi. *Sustainability*, *10*(12), 1–18. https://doi.org/10.3390/su10124720

Cichociński, P., & Dąbrowski, J. (2013). Spatio-Temporal Analysis of the Real Estate Market Using Geographic Information Systems. *Real Estate Management and Valuation*, *21*(2), 73–82. https://doi.org/10.2478/remav-2013-0019

Coakley, J. R., & Brown, C. E. (2000). Artificial neural networks in accounting and finance: modeling issues. *International Journal of Intelligent Systems in Accounting, Finance & Management, 9*(2), 119–144. https://doi.org/10.1002/1099-1174(200006)9:2<119::AID-ISAF182>3.0.CO;2-Y

Cui, N., Gu, H., Shen, T., & Feng, C. (2018). The Impact of Micro-Level Influencing Factors on Home Value: A Housing Price-Rent Comparison. *Sustainability*, *10*(12), 1–23. https://doi.org/10.3390/su10124343

Del Giudice, V., De Paola, P., & Forte, F. (2017). Bayesian neural network models in the appraisal of real estate properties. *International Conference on Computational Science and Its Applications*, 478–489. Cham: Springer. https://doi.org/10.1007/978-3-319-62398-6_34

Delbari, M., Afrasiab, P., & Jahani, S. (2013). Spatial interpolation of monthly and annual rainfall in northeast of Iran. *Meteorology and Atmospheric Physics*, *122*, 103–113. https://doi.org/10.1007/s00703-013-0273-5

Devaux, N., Berthold, E., & Dubé, J. (2018). Economic Impact of a Heritage Policy on Residential Property Values in a Historic District Context: The Case of the Old City of Quebec. *The Review of Regional Studies*, *48*, 279–297.

Diao, M. (2015). Selectivity, spatial autocorrelation and the valuation of transit accessibility. *Urban Studies*, *52*(1), 159–177.

Dubin, R A. (1998). Spatial Autocorrelation: A Primer. *Journal of Housing Economics*, *7*, 304–327. https://doi.org/10.1177/0042098014523686

Dubin, R A. (1998). Spatial Autocorrelation: A Primer. *Journal of Housing Economics*, *7,* 304-327. https://doi.org/10.1006/jhec.1998.0236

Dubin, Robin A. (1992). Spatial autocorrelation and neighborhood quality. *Regional Science and Urban Economics*, *22*(3), 433–452. https://doi.org/10.1016/0166-0462(92)90038-3

Gambo, Y. L. (2012). Hedonic Price Modeling of the Influence of Violent Ethno-Religious Conflict on Residential Property Values in Bauchi Metropolis, Nigeria. *Journal of Sustainable Development*, *5*(9), 85–97. https://doi.org/10.5539/jsd.v5n9p85

Ge, J. (2017). Endogenous rise and collapse of housing price. *Computers, Environment and Urban Systems*, *62*, 182–198. https://doi.org/10.1016/j.compenvurbsys.2016.11.005

Goodman, A. C., & Thibodeau, T. G. (1995). Age-Related Heteroskedasticity in Hedonic House Price Equations. *Journal of Housing Research*, *6*(1), 25–42.

Guan, J., & Gao, J. (2018). Time and Space Analysis of House Price in Mainland China in the Last 10 Years. *Modern Economy*, *09*(09), 1520–1532. https://doi.org/10.4236/me.2018.99096

Gulyani, S., Talukdar, D., & Bassett, E. M. (2018). A sharing economy? Unpacking demand and living conditions in the urban housing market in Kenya. *World Development*, *109*, 57–72. https://doi.org/10.1016/j.worlddev.2018.04.007

Hanson, A., & Hawley, Z. (2011). Do landlords discriminate in the rental housing market? Evidence from an internet field experiment in US cities. *Journal of Urban Economics*, *70*(2–3), 99–114. https://doi.org/10.1016/j.jue.2011.02.003

Helbich, M., Brunauer, W., Vaz, E., & Nijkamp, P. (2014). Spatial Heterogeneity in Hedonic House Price Models: The Case of Austria. *Urban Studies*, *51*(2), 390–411. https://doi.org/10.1177/0042098013492234

Hill, R. J., & Scholz, M. (2017). Can Geospatial Data Improve House Price Indexes? A Hedonic Imputation Approach with Splines. *Review of Income and Wealth*, *64*(4), 737–756. https://doi.org/10.1111/roiw.12303

Hu, S., Cheng, Q., Wang, L., & Xu, D. (2013). Modeling land price distribution using multifractal IDW interpolation and fractal filtering method. *Landscape and Urban Planning*, *110*, 25–35. https://doi.org/10.1016/j.landurbplan.2012.09.008

Huang, W.-L., Lin, W.-Y., & Ning, S.-L. (2018). The effect of economic policy uncertainty on China's housing market. *The North American Journal of Economics and Finance*, in Press. https://doi.org/10.1016/j.najef.2018.09.008

Iliopoulou, P., & Stratakis, P. (2018). *Spatial analysis of housing prices in the Athens Region, Greece*. 10.

Jung, E., & Yoon, H. (2018). Is Flood Risk Capitalized into Real Estate Market Value? A Mahalanobis-Metric Matching Approach to the Housing Market in Gyeonggi, South Korea. *Sustainability*, *10*(11), 1–17. https://doi.org/10.3390/su10114008

Kauko, T. (2003). On current neural network applications involving spatial modelling of property prices. *Journal of Housing and the Built Environment*, *18*, 159–181. https://doi.org/10.1023/A:1023977111302

Kauko, T., Hooimeijer, P., & Hakfoort, J. (2002). Capturing Housing Market Segmentation: An Alternative Approach based on Neural Network Modelling. *Housing Studies*, *17*(6), 875–894. https://doi.org/10.1080/02673030215999

Kemiki, O., Ojetunde, I., & Ayoola, A. (2014). The Impact of Noise and Dust Level on Rental Price of Residential Tenements around Lafarge Cement Factory in Ewekoro Town, Nigeria. *Ethiopian Journal of Environmental Studies and Management*, *7*(2), 108–116. https://doi.org/10.4314/ejesm.v7i2.1

Khalafallah, A. (2008). Neural network based model for predicting housing market performance. *Tsinghua Science and Technology*, *13*(S1), 325–328. https://doi.org/10.1016/S1007-0214(08)70169-X

Kim, H.-S., Lee, G.-E., Lee, J.-S., & Choi, Y. (2019). Understanding the local impact of urban park plans and park typology on housing price: A case study of the Busan metropolitan region, Korea. *Landscape and Urban Planning*, *184*, 1–11. https://doi.org/10.1016/j.landurbplan.2018.12.007

Kuntz, M., & Helbich, M. (2014). Geostatistical mapping of real estate prices: An empirical comparison of kriging and cokriging. *International Journal of Geographical Information Science*, *28*(9), 1904–1921. https://doi.org/10.1080/13658816.2014.906041

Latinopoulos, D. (2018). Using a spatial hedonic analysis to evaluate the effect of sea view on hotel prices. *Tourism Management*, *65*, 87–99. https://doi.org/10.1016/j.tourman.2017.09.019

Li, S., Ye, X., Lee, J., Gong, J., & Qin, C. (2017). Spatiotemporal Analysis of Housing Prices in China: A Big Data Perspective. *Applied Spatial Analysis and Policy*, *10*(3), 421–433. https://doi.org/10.1007/s12061-016-9185-3

Li, X., & Tang, Y. (2018). When natives meet immigrants in public and private housing markets. *Journal of Housing Economics*, *41*, 30–44. https://doi.org/10.1016/j.jhe.2017.08.003

Li, Y., Zhang, H., Yang, F., & Wang, Y. (2014). Applications of Artificial Neural Networks in the Identification of Real Estate Cycles: Evidence from China. In D. Yang & Y. Qian (Eds.), *Proceedings of the 18th International Symposium on Advancement of Construction Management and Real Estate* (pp. 185–195). https://doi.org/10.1007/978-3-642-44916-1_19

Liao, W.-C., & Wang, X. (2012). Hedonic house prices and spatial quantile regression. *Journal of Housing Economics*, *21*(1), 16–27. https://doi.org/10.1016/j.jhe.2011.11.001

Liebelt, V., Bartke, S., & Schwarz, N. (2018). Hedonic pricing analysis of the influence of urban green spaces onto residential prices: The case of Leipzig, Germany. *European Planning Studies*, *26*(1), 133–157. https://doi.org/10.1080/09654313.2017.1376314

Limsombunc, V., Gan, C., & Lee, M. (2004). House Price Prediction: Hedonic Price Model vs. Artificial Neural Network. *American Journal of Applied Sciences*, *1*(3), 193–201. https://doi.org/10.3844/ajassp.2004.193.201

Lu, J. (2018). The value of a south-facing orientation: A hedonic pricing analysis of the Shanghai housing market. *Habitat International*, *81*, 24–32. https://doi.org/10.1016/j.habitatint.2018.09.002

Malpezzi, S. (2002). Hedonic Pricing Models: A Selective and Applied Review. In T. O'Sullivan & K. Gibb (Eds.), *Housing Economics and Public Policy* (pp. 67–89). https://doi.org/10.1002/9780470690680.ch5

McCluskey, W. J., Deddis, W. G., Lamont, I. G., & Borst, R. A. (2000). The application of surface generated interpolation models for the prediction of residential property values. *Journal of Property Investment & Finance*, *18*(2), 162–176. https://doi.org/10.1108/14635780010324321

Meese, R., & Wallace, N. (1991). Nonparametric Estimation of Dynamic Hedonic Price Models and the Construction of Residential Housing Prices Indeces. *Real Estate Economics*, *19*(3), 308–332. https://doi.org/10.1111/1540-6229.00555

Mohammed, J. K., & Sulyman, A. O. (2019a). Conventional Approaches and Mechanism to Housing Market Analysis. In L. T. Ajibade, N. B. Tanimowo, G. Amuda-Yusuf, & N. A. Bello (Eds.), *The Proceedings of International Conference of Environmental Sciences* (pp. 255–263). University of Ilorin, Nigeria.

Mohammed, J. K., & Sulyman, A. O. (2019b). Spatio-temporal Analysis of Bida Housing Market using Geographic Information System. In L. T. Ajibade, N. B. Tanimowo, G. Amuda-Yusuf, & N. A. Bello (Eds.), *The Proceedings of International Conference of Environmental Sciences* (pp. 306–316). University of Ilorin, Nigeria.

Moral, F. J. (2008). Comparison of different geostatistical approaches to map climate variables: application to precipitation. *Int. Journal of Climatology*, *30*(4), 620–631. https://doi.org/10.1002/joc.1913

Moulton, M., & Preece, A. (2002). Ann Macintosh, BSc, CEng International Teledemocracy Centre, Napier University, Edinburgh, UK. *Proceedings of ES2001*.

Muehlenbachs, L., Spiller, E., & Timmins, C. (2015). The housing market impacts of shale gas development. *American Economic Review*, *105*(12), 3633–3659. https://doi.org/10.1257/aer.20140079

Oladunni, T., Sharma, S., & Tiwang, R. (2017). A Spatio – Temporal Hedonic House Regression Model. *IEEE International Conference on Machine Learning and Applications*. Presented at the IEEE International Conference on Machine Learning and Applications. https://doi.org/10.1109/ICMLA.2017.00-94

Oluwadamilola, I. (2017). Effect of Socioeconomic Factors on the Rental Values of Accommodation in Lagos Metropolis. *Equatorial Journal of Social Sciences and Human Behaviour*, *2*(3), 106–120.

Paz, P. T. de la, & McGreal, S. (2018). A Re-Assessment of House Price Indices: Evidence from the Spanish Market. *International Journal of Strategic Property Management*, *23*(1), 23–35. https://doi.org/10.3846/ijspm.2019.6366

Razali, M. N., Zulkarnain, S. H., Tarmidi, Z., Maimun, N. H. A., Adnan, Y. Mohd., & Yuzir, M. A. (2018). Property market price response to flood-hazard. *Natural Hazards*, 1–16. https://doi.org/10.1007/s11069-018-3495-5

Renigier-Biłozor, M., Biłozor, A., & Wisniewski, R. (2017). Rating engineering of real estate markets as the condition of urban areas assessment. *Land Use Policy*, *61*, 511–525. https://doi.org/10.1016/j.landusepol.2016.11.040

Sandmo, A. (2014). The Market in Economics: Behavioural Assumptions and Value Judgments. *SSRN Electronic Journal*. https://doi.org/10.2139/ssrn.2432934

Selim, H. (2009). Determinants of house prices in Turkey: Hedonic regression versus artificial neural network. *Expert Systems with Applications*, *36*(2), 2843–2852. https://doi.org/10.1016/j.eswa.2008.01.044

Seo, W. (2008). Spatial impacts of micro neighborhood environments on residential real estate resale values: The importance of physical disorder (The Ohio State University). Retrieved from http://rave.ohiolink.edu/etdc/view?acc_num=osu1228281862

Sopranzetti, B. J. (2015). Hedonic Regression Models. In C. F. Lee & J. Lee (Eds.), *Handbook of Financial Econometrics and Statistics* (pp. 2119–2134). New York: Springer. https://doi.org/10.1007/978-1-4614-7750-1_78

Tu, Y., Sun, H., & Yu, S.-M. (2007). Spatial Autocorrelations and Urban Housing Market Segmentation. *The Journal of Real Estate Finance and Economics*, *34*(3), 385–406. https://doi.org/10.1007/s11146-007-9015-0

Tupenaite, L., Kanapeckiene, L., & Naimaviciene, J. (2017). Determinants of Housing Market Fluctuations: Case Study of Lithuania. *Procedia Engineering*, *172*, 1169–1175. https://doi.org/10.1016/j.proeng.2017.02.136

UN-Habitat. (2011). *Cities and Climate Change: Global Report on Human Settlements 2011* (1st ed.). https://doi.org/10.4324/9781849776936

Wang, Y., Wang, S., Li, G., Zhang, H., Jin, L., Su, Y., & Wu, K. (2017). Identifying the determinants of housing prices in China using spatial regression and the geographical detector technique. *Applied Geography*, *79*, 26–36. https://doi.org/10.1016/j.apgeog.2016.12.003

Wickramaarachchi, N. (2016). Determinants of rental value for residential properties: A land owner's perspective for boarding homes. *Built-Environment Sri Lanka*, *12*(1), 10–22. https://doi.org/10.4038/besl.v12i1.7612

Wu, C., Ye, X., Du, Q., & Luo, P. (2017). Spatial effects of accessibility to parks on housing prices in Shenzhen, China. *Habitat International*, *63*, 45–54. https://doi.org/10.1016/j.habitatint.2017.03.010

Wu, J., Deng, Y., & Liu, H. (2014). House price index construction in the nascent housing market: The case of China. *The Journal of Real Estate Finance and Economics*, *48*(3), 522–545. https://doi.org/10.1007/s11146-013-9416-1

Xiao, Y. (2012). Urban morphology and housing market (PhD Thesis). Cardiff University.

Xiao, Y. (2017). *Urban Morphology and Housing Market*. In *Springer Geography*. https://doi.org/10.1007/978-981-10-2762-8

Xiao, Y., Webster, C., & Orford, S. (2016). Identifying house price effects of changes in urban street configuration: An empirical study in Nanjing, China. *Urban Studies*, *53*(1), 112–131. https://doi.org/10.1177/0042098014560500

Yusuf, A. A., & Resosudarmo, B. P. (2009). Does clean air matter in developing countries' megacities? A hedonic price analysis of the Jakarta housing market, Indonesia. *Ecological Economics*, *68*(5), 1398–1407. https://doi.org/10.1016/j.ecolecon.2008.09.011

Zhang, M., & Zhao, P. (2018). The determinants of informal housing price in Beijing: Village power, informal institutions, and property security. *Cities*, *77*, 117–129. https://doi.org/10.1016/j.cities.2018.01.018

Zhang, Y., Sun, Y., & Stengos, T. (2018). Spatial Dependence in the Residential Canadian Housing Market. *The Journal of Real Estate Finance and Economics, 58*, 223–263. https://doi.org/10.1007/s11146-017-9623-2

Zhang, Z., & Tang, W. (2016). Analysis of spatial patterns of public attention on housing prices in Chinese cities: A web search engine approach. *Applied Geography*, *70*, 68–81. https://doi.org/10.1016/j.apgeog.2016.03.004

Zhou, Z. (2018). Housing market sentiment and intervention effectiveness: Evidence from China. *Emerging Markets Review, 35,* 91–110. https://doi.org/10.1016/j.ememar.2017.12.005

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