PLANNING MALAYSIA:
Journal of the Malaysian Institute of Planners
VOLUME 19 ISSUE 3 (2021), Page 375 – 386

CONSTRUCTING HOUSING PRICE INDEX FOR TERRACED PROPERTIES IN JOHOR BAHRU, MALAYSIA

Wendy Lim Wen Xin[1], Burhaida Burhan[2], Mohd Lizam Mohd Diah[3]

[1,2,3]*Department of Real Estate Management*
Faculty of Technology Management and Business
UNIVERSITI TUN HUSSEIN ONN MALAYSIA

Abstract

Housing is a country's biggest asset. Hence, the pattern of the housing price index (HPI) is an important topic to gain insight into the housing market while identifying the prevailing housing issues. The determinants of housing price vary for each city and state based on the different characteristics in each location. Accordingly, HPI should consider the property's quality differences. Besides, national HPI is insufficient and restricted to the housing price at the state level. Thus, the study focused on constructing a specified HPI model for different cities, districts, and states. Effective HPI can give parties a better idea of the current property market situation and act as an analytical tool in managing the sector. Specifically, the study aims to examine the relationship between the heterogeneity housing attributes and housing prices of the terraced properties in Johor Bahru, Malaysia. Additionally, the study provides detailed information on the key determinants of the housing price variation in Johor Bahru. Hedonic price analysis is useful in constructing HPI, expressing housing price as a function of vector property characteristics. Furthermore, HPI is constructed based on the yearly indices and by pooling the data into certain periods. The results show the percentage of variance explained by the factors of HPI for the terraced properties in Johor Bahru. Correspondingly, the underlying correlation between the tested housing attributes with the housing price is explained through the analysis results.

***Keyword**:* Housing market, housing price index, hedonic analysis, residential property

[2] Senior lecturer at Universiti Tun Hussein Onn Malaysia, Johor. Email: burhaida@uthm.edu.my

HOUSING PRICE INDEX (HPI)

As no two properties are identical due to heterogeneity, housing prices vary based on numerous attributes, such as locational and structural features (Lim et al., 2018). The attributes significantly contribute to the formation of housing prices (Tan, 2010). Essentially, property transaction prices are reflected through structural and locational attributes, such as lot area size, tenure, property age, proximity to the central business district (CBD), neighbourhood, facilities, transit stations, and others (Dziauddin, Ismail and Othman, 2015; Wilhelmsson, 2000; Laakso and Loikkanen, 1995). Summarily, regressing the property locational and structural attributes against the transaction price enables estimating the significant effects of these traits on the property price.

The HPI is a widely used indicator in the real estate property market that portrays the general fluctuation of housing prices across the period. Besides, HPI is a broad indicator of the operation and transaction of the property market (Kassim, Redzuan and Harun, 2017). Rosen (1974) stated that HPI is computed based on the hedonic regression model with the working hypothesis that housing price encloses significant determinants by considering the property's locational and structural attributes.

Issues of Housing Price Index

The HPI is more challenging to measure than other goods and assets due to three key distinguishing characteristics. Firstly, properties are heterogeneous, meaning that every property has a different housing price summed up by different combinations of structural and locational attributes. Abdul Rahman et al. (2019) suggested that the sampled HPI could be a weak indicator of all housing prices, and predicting the sales prices of a given property from the price of another is unfair. Additionally, simple HPI conducted based on mean and median excludes all the property attributes of the dwellings (Burhan, 2014). Thus, no exact single HPI works as the best measure of central tendency for the properties based on the various attributes.

Secondly, past studies express that the housing price of a given property cannot be simply observed without being sold or transacted. Generally, properties are commonly transacted at an agreed price upon the consensus of both parties through negotiation or auction, making the advertised housing price a poor substitute for the eventual selling price (Burhan, 2014; Wood, 2005). Thirdly, properties are generally sold infrequently (Chandler and Disney, 2014; Wood, 2005). Hence, the illiquidity of the property market is explained through the infrequently transacted dwellings, as the types of property sold at different times may vary.

Consequently, changes in the reported HPI between years may be influenced by the different composition of property sold rather than reflecting on the actual changes in the property market (Nagaraja, Brown and Wachter, 2014).

Thus, the property market cycle is unpredictable, leading to volatility in the real estate market (Rosmera, Mohd Diah and Omar, 2012). Based on past studies, many determinants or property attributes are included to examine its relationship with the housing price. Nevertheless, Sutton (2002) and Chen and Patel (1998) argued that the housing price model in the market failed to clarify the correlation between housing price and the determinants due to confusion and uncertainty.

Chen and Patel (1998) supported the argument, indicating possible reasons for the failure resulting from misunderstanding the interrelation between housing price and the tested determinants. As the nature of the property market is complex and always fluctuating, substantial uncertainty exists. Maclennan (1994) cited that "*the housing market is a large sector of the economy and it is highly possible that the housing market and the economy interact. Although the feedback mechanism is possible, it is not very clear. It is not only important to determine a timing relationship, but also a direct relationship between house price and its aggregate determinant series*".

Presently, the relationship between property attributes and housing price is still a debatable issue in the property market. Every property has a different housing price summed up by the various combinations of property characteristics and attributes. Moreover, housing price factors vary for each city and state due to its different characteristics in every location. Therefore, the national housing price is insufficient and limited to the housing price at the state level. Thus, the study emphasises the importance of constructing different models for different cities or states in the country.

The study evaluates the time-series aggregation effects on the HPI in Johor Bahru by using a comprehensive transaction-based data set from 2009 to 2018. The hedonic approach enables a full appraisal and estimation of the property attributes on the housing price. Besides, the analysis results focus on the R-squared (R^2) value for each selected period. The R^2 value is the coefficient of determination, the proportion of variance in the dependent variable explained by the independent variables (Cameron and Windmeijer, 1997). Hence, the analysis results measure the percentage of variance explained by the property attributes of the HPI.

HEDONIC PRICE ANALYSIS

Basically, the hedonic method is a widely used analysis for constructing HPI (Burhan, 2014; Rosmera, Mohd Diah and Omar, 2012). Many researchers apply the hedonic price model to examine the relationship between property attributes and housing price. Previously, the hedonic pricing model was implemented expansively into the housing market research and explored the link between the housing price and the housing characteristics. The model also examines housing demand for attributes and guides housing price (Fenwick, 2013). The hedonic

price analysis is performed by referring to the multiple regression technique based on the correlation method (Md Yusof and Ismail, 2012).

Two main types of variables are identified for the analysis, i.e., independent variables and dependent variable. It is important to carefully determine the variables that contribute to the housing price. Subsequent effect, if the essential variables are not being identified, it will lead to omitted variables bias (Rosmera, Mohd Diah and Omar, 2012).

Two main types of variables are identified for the analysis: independent variables and dependent variables. Significantly, the variables that contribute to the housing price must be identified, failing which lead to omitted variables bias (Rosmera, Mohd Diah and Omar, 2012). Property housing price is commonly used to model the dependent variable to determine the correlation or contribution of each independent variable in price variation (Haron and Ibrahim, 2019; Md Yusof and Ismail, 2012). Meanwhile, independent variables are related to two categories: locational attributes of property (distance to CBD, area category) and structural attributes of property (lot area size, building size, property type) (Owusu-Ansah and Abdulai, 2014; Watkins, 1999).

Nonetheless, no specific or compulsory variables are included when constructing HPI for the property market (Dorsey *et al*., 2010; Osland, 2010). The common variables mainly used to describe the physical characteristics are listed as follows. The locational and structural attributes often incorporated in the regression model are lot area size (specifically for landed property, such as terraced, detached); the number of storeys for strata property (specifically for high rise units only, such as flat, condominium and apartment); building size; building age; distance to the nearest town centre; property type; building condition; type of tenure (freehold or leasehold); and neighbourhood classification.

Generally, housing is heterogeneous goods, with each unit comprising a group of unique attributes and characteristics. Each attribute included could have its implicit price. Hedonic price analysis enables further identification of a substantial relationship between housing price and its characteristics with the following simplified equation (Ebru and Eban, 2009):

$$\mathbf{HP} = x_i\beta + \varepsilon_i$$

where HP = housing price, x_i = set of independent variables, β = coefficient matrix and ε_i = error term.

Aggregating hedonic price analysis enables the researchers to identify the extent of selected attributes or characteristics in the housing price variation. The hedonic analysis could also provide significant evidence and detailed assumption on the impact of each attribute on the housing prices. Studies propose that the hedonic analysis of each housing attribute is governed by its supply and demand,

with its own '*market*'. As housing is heterogeneous, each housing attribute would have its own '*hedonic price*' (Burhan, 2014). Thus, one can create HPI based on hedonic price analysis, and this analysis could aid in examining the volatility of the overall housing market condition. Ultimately, the analysis enables researchers and relevant authorities to gain better insight into a particular property market.

ANALYSIS AND RESULTS

Model 1: Regression Analysis for Terraced Property from the Year 2009-2018

In order to construct Model 1, multiple regression analysis was conducted based on the property transaction dataset obtained from the Department of Valuation and Property Services (JPPH). The regression analysis included all the transacted terraced properties in Johor Bahru for the past ten years, 2009 to 2018.

Table 1: Regression Analysis Summary for Model 1 Before Data Cleaning

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.534[a]	.285	.285	188083.770

a. Predictors: (Constant), Year (Y), Building Size (BS), Type of Construction (TC), Lot Area Size (LS), Area Category (ACT), No. Bedroom (NB), Property Condition (PC), Tenure (T), No. Storey (NS), Subdistrict (S), Area Classification (ACL), Completion Date (CD), Property Type (PT), Valuation Date (VD)
b. Dependent Variable: Housing Price (HP)

Source: Researcher's study, 2020

Table 2: Regression Analysis Summary for Model 1 After Data Cleaning

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.773[a]	.598	.598	131051.651

a. Predictors: (Constant), Y, BS, TC, LS, ACT, NB, PC, T, NS, S, ACL, CD, PT, VD
b. Dependent Variable: HP

Source: Researcher's study, 2020

Based on **Table 2**, the R^2 value was approximately 0.598, which could evaluate the overall goodness of fit for Model 1. The results showed that 59.8% of the variation of housing prices could be explained by the 14 independent variables. Referring to **Table 1**, the model before data cleaning yielded an R^2 value of approximately 0.285 or 28.5%. Thus, the R^2 value for Model 1 achieved a marked improvement of 31.3% by removing missing values and unwanted observations from the dataset.

Table 3: Coefficient Summary for Model 1 After Data Cleaning

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	-23698969.20	2837106.98		-8.35	.000
	Subdistrict	-1548.91	211.91	-.020	-7.31	.000
	Tenure	-20545.10	1835.11	-.029	-11.20	.000
	Property Condition	3943.23	408.81	.024	9.65	.000
	Type of Construction	13302.95	9996.35	.003	1.33	.183
	Lot Area Size	655.67	7.22	.236	90.77	.000
	Building Size	2106.90	17.76	.422	118.62	.000
	No. Bedroom	48637.45	1246.82	.120	39.01	.000
	Property Type	-17394.34	2749.72	-.040	-6.33	.000
	No. Storey	-6955.36	2770.89	-.016	-2.51	.012
	Completion Date	3656.33	67.43	.169	54.22	.000
	Valuation Date	.001	.000	.377	16.70	.000
	Area Classification	21183.34	639.50	.093	33.13	.000
	Area Category	6775.69	588.56	.033	11.51	.000
	Year	1643.33	1790.24	.021	.92	.359

a. Dependent Variable: Housing Price

Source: Researcher's study, 2020

For **Table 3**, the results indicated that 12 of the 14 variables were statistically significant and good predictors for the variation of housing price as the corresponding *p-value* was highly significant and less than the alpha value of 0.05 ($p < 0.05$). Hence, the *Type of Construction* (TP) and *Year* (Y) were not statistically significant for Model 1 as its *p-value* was larger than 0.05. The R^2 value for Model 1 is 59.8%, suggesting that about 40.2% of the housing price behaviour was not explained and undiscussed by the model. As some outliers and unexplained variables were identified while constructing Model 1, the study proposes to further the analysis by dividing the aggregation of the dataset into independent years for an in-depth analysis.

Model 2: Regression Analysis for Terraced Property Per Annum Basis

The study aims to divide the property transaction dataset into its independent year, one multiple regression analysis for each year as an in-depth evaluation for Model 2.

Table 4: Regression Analysis Summary for Model 2

Year	R	R Square	Adjusted R Square	Std. Error of the Estimate	N
2009	.756[a]	.571	.570	51249.175	5534
2010	.726[a]	.527	.526	66544.367	6087
2011	.737[a]	.544	.543	64805.029	5924
2012	.709[a]	.503	.502	75364.017	4278
2013	.699[a]	.488	.488	159881.220	11702
2014	.738[a]	.545	.544	149830.532	8624
2015	.778[a]	.606	.605	141447.948	8045
2016	.759[a]	.575	.575	141039.285	6340
2017	.744[a]	.554	.553	131981.039	6159
2018	.756[a]	.572	.571	113382.065	4055

a. Predictors: (Constant), Y, BS, TC, LS, ACT, NB, PC, T, NS, S, ACL, CD, PT, VD
b. Dependent Variable: HP

Source: Researcher's study, 2020

Table 4 above tabulates the movement for the model of fitness throughout the determined independent time frame. Calhoun *et al.* (1995) and Burhan (2014) mentioned that when the time interval is shortened in aggregation, the variance of housing prices should increase. Nonetheless, the results indicated that the R^2 value for each independent year was slightly lower than the R^2 value of Model 1 (0.598). The average R^2 value of the independent year was approximately 0.549, as the lowest R^2 value was 0.488 in 2013. Nevertheless, the R^2 value for 2015 is an exception, with the highest recorded value within the ten years, at 0.606, whereby 60.6% of the variation of housing price is explained by the included independent variables. As the R^2 value for Model 2 was between low and moderate effect size, the study proposed conducting a stepwise regression to identify and delineate the statistically significant variables with the variation of housing price for terraced properties in Johor Bahru.

Table 5: Stepwise Regression Analysis Summary for Model 2

Year	R Square	R Square (Stepwise)	No. of Predictors Entered	No. of Predictors Removed
2009	.571	.571	14	4
2010	.527	.526	14	5
2011	.544	.544	14	3
2012	.503	.503	14	2
2013	.488	.488	14	5
2014	.545	.544	14	3
2015	.606	.606	14	2
2016	.575	.575	14	5
2017	.554	.553	14	6
2018	.572	.572	14	5

a. [2009]Predictors: (Constant), BS, LS, NB, CD, NS, ACL, VD, PC, ACT, S
a. [2010]Predictors: (Constant), BS, LS, NB, CD, ACL, S, NS, VD, PC
a. [2011]Predictors: (Constant), BS, LA, NB, CD, ACL, NS, VD, ACT, S, PT, T
a. [2012]Predictors: (Constant), BS, LS, NB, CD, NS, ACL, VD, S, T, PC, PT, ACT
a. [2013]Predictors: (Constant), BS, LS, CD, ACL, NB, VD, PC, ACT, S
a. [2014]Predictors: (Constant), BS, LS, CD, ACL, NB, NS, VD, ACT, S, T, PT
a. [2015]Predictors: (Constant), BS, LS, NB, T, VD, CD, ACL, PC, S, ACT, PT, NS
a. [2016]Predictors: (Constant), BS, LS, NB, ACL, CD, T, PT, ACT, VD
a. [2017]Predictors: (Constant), BS, LS, ACL, NB, CD, VD, NS, T
a. [2018]Predictors: (Constant), BS, LS, NB, ACL, CD, NS, VD, T, PT
b. Dependent Variable: HP

Source: Researcher's study, 2020

Stepwise regression is an analysis conducted when many variables and authors identify a useful subset of predictors to narrow down the independent variables into a list of the top predictors of housing price variation. In order to reduce the effect of multicollinearity, the variables strongly correlated to other variables will be removed (Makido, Dhakal and Yamagata, 2012; Yen and Tan, 1999). The results in **Table 5** found almost zero to less than 0.01 difference for the R^2 value after stepwise regression.

Based on Burhan (2014), the implicit assumption of constant quality is difficult to verify with small to almost no differences in the variance across the years and models. Hence, the study suggests exploring the later years or the recent year of the database. The proposal comprehensively highlights the predictors of that holding year instead of the whole database set, whereby bias may have occurred in the earlier years. Thus, the study further discussed the results from the stepwise regression for the variation of housing price in Johor Bahru for 2018, as in **Table 6**.

Table 6: Stepwise Regression Coefficient Summary for Model 2

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	-20007266.44	3211764.40		-6.23	.000
	Building Size	2095.85	67.41	.499	31.09	.000
	Lot Area Size	888.75	31.73	.310	28.01	.000
	No. Bedroom	48312.80	4445.08	.141	10.87	.000
	Area Classification	24116.44	2117.70	.125	11.39	.000
	Completion Date	2756.87	227.69	.151	12.11	.000
	No. Storey	-39947.56	9365.04	-.112	-4.27	.000
	Valuation Date	.001	.000	.047	4.56	.000
	Tenure	-20312.24	7050.39	-.030	-2.88	.004
	Property Type	18237.73	9049.61	.051	2.02	.044
	Excluded Variables			Beta In		
	Subdistrict			-.002[j]	-1.91	.848
	Property Condition			-0.01[j]	-.07	.947
	Area Category			.011[j]	.97	.334

Source: Researcher's study, 2021

The most statistically significant variables for the variation of housing price in 2018 are identified as follows, with eight structural attributes and one locational factor.

Table 7: Predictors for Model 2

Predictors	Descriptions
(a) Building Size	It has a significant impact on housing prices because a larger home has a higher value and worth.
(b) Lot Area Size	Property is estimated based on the price per square meter. Hence, the larger the area, the higher the value of the property.
(c) Number of Bedroom	The number of bedrooms is highly related to predictors in (a) and (b), as the larger the area acquired, the greater the number of bedrooms.
(d) Area Classification	Properties in areas with facilities, amenities, and commercial centres have higher values than rural properties.
(e) Completion Date	It provides insight details of the property age and condition.
(f) Number of Storey	The greater the number of housing storey, the larger the property size.
(g) Valuation Date	It is related to the market value during that period.

Source: Researcher's study, 2020

Table 7 (continued): Predictors for Model 2

Predictors	Descriptions
(h) Tenure	Ownership of freehold property remains intact with its titleholder with no time limit unless transferred legally to another party. Hence, providing more value in terms of housing price compared to leasehold ownership.
(i) Property Type	The physical characteristics of a double-storey terraced house are larger and greater than a single-storey terraced house, such as area size and building size. Refer to predictors (a), (b), (c), and (f).

Source: Researcher's study, 2020

Stepwise regression excluded certain variables as each irrelevant predictor would decrease the precision of the estimated coefficients and predicted values. Based on **Table 6**, the *p-values* for the three predictors, *Subdistrict* (S), *Property Condition* (PC) and *Area Category* (ACT), were above the alpha value of 0.05. Hence, the predictors were not statistically significant to the model and were excluded from the analysis.

Table 8: Housing Price Index (HPI)

Model (Year)	Median of Property Price (RM)	Index
2009	170,000	100.00
2010	180,000	105.88
2011	185,000	108.82
2012	210,000	123.53
2013	300,000	176.47
2014	300,000	176.47
2015	350,000	205.88
2016	400,000	235.29
2017	409,000	240.59
2018	450,000	264.71

Remark: Year 2009 as base.

Source: Researcher's study, 2020

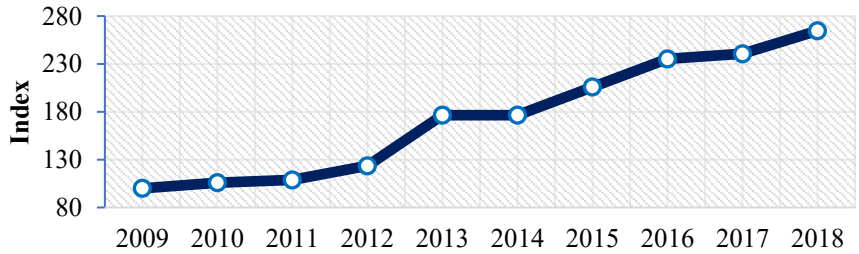

Figure 1: Housing Price Index (HPI) for the Year 2009 - 2018
Source: Researcher's study, 2020

Based on the two analyses conducted, the R^2 value for both models was generally in between low and moderate effect size. As the tabulated R^2 value was weak and less convincing, further tests should be considered and applied to increase the efficiency of the overall goodness of fit. Besides, extended future research should be conducted by considering other omitted variables to discover more about the underlying relationship of the variables towards housing prices.

CONCLUSION

The results signify that the most significant variables identified for the variation of housing price are structural characteristics, such as lot area size, building size and the number of storeys. The results also show that only approximately 50% of the variation in housing price were explained by the model with the current list of independent variables. Hence, about 50% of the behaviour of housing prices was not explored nor explained by the model. Past studies mentioned that structural and locational attributes of the property are the two crucial predictors for the housing price. Thus, the study strongly suggests performing other extended analyses by including the omitted variables, such as environmental and neighbourhood attributes, in the analysis model. As locational characteristics from the current dataset were inadequate for the analysis, the study aims to obtain and include another necessary dataset. The omitted variables from the new dataset could provide useful insights and discuss its extent on the variation of housing price.

ACKNOWLEDGEMENTS

The authors would like to thank the Ministry of Higher Education Malaysia for supporting this research under Fundamental Research Grant Scheme Vot No. FRGS/1/2019/SS08/UTHM/02/1 and partially sponsored by Universiti Tun Hussein Onn Malaysia. In addition, the authors gratefully acknowledge NAPIC and JPPH for providing the data used in this research.

REFERENCES

Abdul Rahman, S.N. *et al.* (2019). The Artificial Neural Network Model (ANN) for Malaysian Housing Market Analysis. *Journal of the Malaysian Institute of Planners*, *17(1)*, pp. 1-9.

Burhan, B. (2014). *Spatial Mechanism of Hedonic Price Functions for Housing Submarket Analysi*s. Saga University: Ph.D Thesis.

Chandler, D. & Disney, R. (2014). *Measuring House Prices: A Comparison of Different Indices*. London: The Institute for Fiscal Studies.

Chen, M.C. & Patel, K. (1998). House Price Dynamics and Granger Causality: An Analysis of Taipei New Dwelling Market. *Journal of The Asian Real Estate Society*, *1(1)*, pp. 101-126.

Dorsey, R.E. *et al.* (2010). Hedonic Versus Repeat-Sales Housing Price Indexes For Measuring The Recent Boom-Bust Cycle. *Journal of Housing Economics*, *19(2)*, pp. 75-93.

Dziauddin, M.F., Ismail, K., & Othman, Z. (2015). Analysing The Local Geography Of The Relationship Between Residential Property Prices And Its Determinants. *Bulletin of Geography: Socio–economic Series*, *28*, pp. 21-35.

Ebru, C. & Eban, A. (2009). Determinants of House Prices in Istanbul: A Quartile Regression Approach. *Quality and Quantity*, *45(2)*, pp. 305-317.

Fenwick, D. (2013). Uses of Residential Property Price Indices. in OECD, *et al*., *Handbook on Residential Property Price Indices*. Eurostat, Luxembourg. pp. 15-20.

Haron, R. & Ibrahim, K. (2019). Residential Property Price Hike and Speculation. *Journal of the Malaysian Institute of Planners*, *17(1)*, pp. 328-337.

Kassim, S., Redzuan, N.H. & Harun, N.Z. (2017). What Drives House Price in Malaysia? In Search of An Alternative Pricing Benchmark for Islamic Home Financing. *Planning Malaysia: Journal of The Malaysian Institute of Planners*, *15(4)*, pp. 21-34.

Laakso, S. & Loikkanen, H.A. (1995). Finnish Homes – Through Passages or Traps. *Real Estate Economics*, *23(4)*, pp. 475-495.

Lim, X.Y. *et al*. (2018). Factors Determining the Demand for Affordable Housing. *Journal of the Malaysian Institute of Planners*, *16(2)*, pp. 109-118.

Maclennan, D. (1994). *A Competitive UK Economy: Challenges for Housing Policy*. United Kingdom: Joseph Rowntree Foundation.

Md Yusof, A. & Ismail, S. (2012). Multiple Regressions in Analysing House Price Variations. *Communicatios of the IBIMA*.

Nagaraja, C.H., Brown, L.D. & Wachter, S.M. (2014). Repeat Sales House Price Index Methodology. *Journal of Real Estate Literature*, *22*.

Osland, L. (2010). An Application of Spatial Econometrics in Relation to Hedonic House Price Modelling. *Journal of Real Estate Research*, *32(3)*, pp. 289-320.

Owusu-Ansah, A. & Abdulai, R.T. (2014). Producing Hedonic Price Indices for Developing Markets. Explicit Time Variable Versus Strictly Cross-Sectional Models. *International Journal of Housing Markets and Analysis*, *7(4)*, pp. 444-458.

Rosmera, N.A., Mohd Diah, M.L. & Omar, A.J. (2012). The Revisited of Malaysian House Price Index. *Proceedings International Conference of Technology Management, Business and Entrepreneurship 2012*. Melaka: Faculty of Technology Management, Business and Entrepreneurship. pp. 656-667.

Sutton, G.D. (2002). Explaining Changes in House Prices. *BIS Quarterly Review September 2002*, pp. 46-55.

Tan, T.H. (2010). The Impact of Neighborhood Types on The Prices of Residential Properties. *Sunway Academic Journal*, *7*, pp. 77-88.

Watkins, C. (1999). Property Valuation and the Structure of Urban Housing Markets. *Journal of Property Investment and Finance*, *17(2)*, pp. 157-173.

Wilhelmsson, M. (2000). The Impact of Traffic Noise on The Values of Single-Family Houses. *Journal of Environmental Planning and Management*, *43(6)*, pp. 799-815.

Wood, R. (2005). A Comparison of UK Residential House Price Indices. in Bank for International Settlements (ed.). *Real Estate Indicators and Financial Stability*. Bank for International Settlements. pp. 212-227.

Received: 12th July 2021. Accepted: 23rd Sept 2021

