PLANNING MALAYSIA:
Journal of the Malaysian Institute of Planners
VOLUME 19 ISSUE 3 (2021), Page 438 – 448

A REVIEW OF SPATIAL ECONOMETRICS IN EXPLICIT LOCATION MODELLING OF COMMERCIAL PROPERTY MARKET

Hamza Usman[1], Mohd Lizam[2], Burhaida Bint Burhan[3]

[1,2,3]*Faculty of Technology Management and Business*
UNIVERSITI TUN HUSSEIN ONN MALAYSIA
[1]*Department of Estate Management & Valuation*
ABUBAKAR TAFAWA BALEWA UNIVERSITY, BAUCH, NIGERIA

Abstract

'Location, location, location' is a real property parlance mostly used to describe the influence of location in the property market. Location is mainly considered as the most significant influencer of commercial property prices. Location is modelled traditionally using hedonic pricing model by either proxy location dummies or distances relative to other neighbourhood features. This was shown to be inadequate due to spatial autocorrelation and heterogeneity inherent in spatial data, which jeopardises the estimates' consistency. Consequently, spatial econometrics is used to explicitly model location into property pricing by controlling spatial effects of autocorrelation and heterogeneity. Housing studies dominate the use of this approach with limited application in the commercial property market. This paper reviewed spatial econometrics and found that the commercial property market exhibits significant spatial dependence and heterogeneity. Accounting for such effects improves model accuracy significantly. It, therefore, recommends increase use of spatial econometrics in commercial property market modelling.

***Keyword**:* Location, Spatial Econometrics, Commercial Property Market, Hedonic Pricing Modelling, Spatial dependence

[1] PhD Graduand at Universiti Tun Hussein Onn Malaysia (UTHM); Email: hamzeeusm@gmail.com

INTRODUCTION

The strategic prominence of the commercial property to the world market has been noted in the literature (Usman & Lizam, 2020; Jeong & Kim, 2011; Raposo & Evangelista, 2017). The commercial property market, like the residential counterpart, is imperfect. Commercial properties have high information asymmetry, high cost of transactions, highly heterogeneous, relative low liquidity and are rarely traded (Beracha, Hardin III, & Skiba, 2018; Chegut, Eichholtz, & Rodrigues, 2015; Hardin III, Jiang, & Wu, 2017; Wiley, 2017). These features of the commercial property make it relatively volatile. Similarly, besides heterogeneity and thinness, a different characteristic of commercial property is the distinctiveness of each commercial property's location (Chegut, Eichholtz, & Rodrigues, 2013; Chiang, 2016). This characteristic makes the location an influential factor in modelling the commercial property market. It is also the reason why location is considered as one of the most critical determinants of commercial property prices (Bhattacharya, Lamond, Proverbs, & Hammond, 2013; Li, He, Xu, Wang, & He, 2013; Droj & Droj, 2015; Hayunga & Pace, 2010; Özyurt, 2013, 2014). This, therefore, underscore the necessity for modelling the commercial property market such that the state of the market and performance of the property market is reflected in the pricing (Corgel, Liu, & White, 2015).

Traditionally, the hedonic pricing model is used to model commercial property market. The composites of properties – location characteristics, neighbourhood attributes, and physical characteristics – constitute the property price (Noh, 2019; Usman, Lizam, & Adekunle, 2020; Usman, Lizam, & Burhan, 2021; Zhang, Zheng, Sun, & Dai, 2019). While the neighbourhood attributes and physical characteristics are relatively straightforward to model in HPM, the location is more challenging to model objectively and objectively (Özyurt, 2014). The traditional location modelling using the hedonic has not explicitly accounted for location impact on commercial property prices even though spatial dispersion of commercial property prices is imminent in the market (Droj & Droj, 2015; Özyurt, 2014). Alternatively, spatial analytical techniques are developed to account for location effect in real estate market modelling explicitly and are shown to improve the accuracy of price prediction (Aliyu, Sani, Usman, & Muhammad, 2018; Noh, 2019; Seo, Salon, Kuby, & Golub, 2019; Usman, Lizam, & Adekunle, 2020). However, the application of explicit spatial treatment of location is skewed towards the residential market with relatively scarcer research works on the commercial property market (Montero-Lorenzo, Larraz-Iribas, & Paez, 2009; Özyurt, 2014). Consequently, this paper reviewed the application of spatial econometric approaches in explicit location modelling of the commercial property market.

LOCATION AND COMMERCIAL PROPERTY MARKET

The phrase 'location, location, location' is widely held parlance among real estate professionals to symbolise location's influence on property prices (Orford, 2017; Özyurt, 2014). Locations are immobile, fixed, and distinctive. Spatially, no property is identically the same as others (Wyatt, 2010). Such distinctiveness of location exerts a substantial effect on property prices with the consequent concerns to all stakeholders in the property market (Orford, 2017). Location is interrelated to local amenities, social ties, and environmental factors. These form positive and negative externalities and affect commercial property prices differently.

The mid-20th-century urban economic theories underpin the modelling property market location. The theories emphasised the trade-off between space relating to Central Business District (CBD) and accessibility (Alonso, 1964; Ibeas, Cordera, Dell'Olio, Coppola, & Dominguez, 2012). High accessibility attracts higher property prices due to accessibility premium (Chiarazzo, dell' Olio, Ibeas, & Ottomanelli, 2014; Muth, 1969). The commercial property market is more sensitive to the influence of location on prices than other property types markets. This is partly because location factors such as access to customers, traffic, market access, employment centres and other location factors determine the acquisition of commercial properties.

Consequently, valuers consider location factors seriously when modelling the property market. In such consideration, the main concern is how to incorporate location into the commercial property market modelling.

COMMERCIAL PROPERTY MARKET LOCATION MODELLING

Commercial properties are modelled traditionally using the conventional hedonic pricing model. This is a quantitative concept and requires a quantitative analysis technique (Bawuro, Shamsuddin, Wahab, & Usman, 2019). Property prices in HPM are treated as the function of the properties' neighbourhood characteristics, location factors and physical attributes (Usman, Lizam, & Burhan, 2020b). Several previous studies have modelled property markets empirically (Abdullahi, Usman, & Ibrahim, 2018; Montero-Lorenzo et al., 2009; Özyurt, 2014). The traditional HPM model location implicitly in two ways. Firstly, neighbourhood effects are modelled using location dummies to control their effects on prices (Raposo & Evangelista, 2017). This method, however, does not explicitly account for the specific individual locations in the model and therefore the uniqueness and distinctiveness of each property's spatial identity is not sufficiently accounted for.

Secondly, the HPM implicitly models location by controlling for the relative distance of major spatial landmarks such as CBDs, highways, bus terminals, rail stations, airports, and other externalities to the subject property (Abdullahi et al., 2018; Bujanda & Fullerton Jr., 2018; Usman, Lizam, & Burhan, 2020a). These implicit location modelling methods have some limitations when dealing with spatial data such as commercial properties. The methods do not capture spatial interactions, which affect the resultant predicted prices (Özyurt, 2014). This spatial interaction makes the model's residuals spatially correlated and not random, violating the assumption of uncorrelated error and constant variance of the Ordinary Least Squares (OLS) (Can, 1992; Özyurt, 2014; Pace, Barry, & Sirmans, 1998). The traditional hedonic models do not explicitly control the effect of spatial autocorrelation, spatial dependence, and spatial heterogeneity inherent in real estate data, making the model estimates biased and inconsistent (Chegut, Eichholtz, & Rodrigues, 2015; Pace et al., 1998). With the sophistication of Geographic Information System (GIS) technology to determine exact property location, spatial econometric models are developed to model such location effects explicitly. This made the commercial property location modelling more efficient, reliable and have better predictions (Droj & Droj, 2015; Özyurt, 2014).

MODELLING SPATIAL DEPENDENCE AND HETEROGENEITY IN COMMERCIAL PROPERTY MARKET

The characteristics of the commercial property market include infrequent and thin transactions, heterogeneity, and high information asymmetry (Özyurt, 2014; Tu, Yu, & Sun, 2004). The commercial property market value depends on a comparable transaction within the neighbourhood called the adjacency effect. The adjacency effect may be because property agents or sellers use comparable information of a particular property in arriving at the price of the subject property, thereby leading the price obtained in the property influencing the price of a nearer property in the neighbourhood (Kim et al., 2003; Yu, Pang, et al., 2017). The presence of statutory homogeneous building codes tends to make properties homogenous in a particular neighbourhood (Chegut, Eichholtz, & Rodrigues, 2015). The presence of these property characteristics leads to a correlation in space among property characteristics. Such correlation is called spatial autocorrelation or dependence (Meen, 2016; Noh, 2019).

Based on Tobler's first law of geography, properties that are located closer together are more expected to be interrelated than with farther properties (Liang, Reed, & Crabb, 2017; Tobler, 1970). When a property attribute in a particular location is correlated spatially with similar attributes closeby, spatial autocorrelation occurs (Dziauddin, Powe, & Alvanides, 2014). Spatial dependence, therefore, is the situation where property price is correlated spatially with the prices of closeby properties. On the other hand, spatial heterogeneity is when the association between property attributes and price vary spatially. It happens when estimates for the property feature in the regression vary over a spatial area (Dziauddin et al., 2014).

The existence of spatial autocorrelation, dependence, and heterogeneity in the property market severely affects property pricing estimation. Failure to account for it in modelling the property prices leads to spurious, distorted, biased and inconsistent parameter estimates (Anselin, 2010; Noh, 2019; Pace et al., 1998; Yu, Pang, et al., 2017). Spatial econometrics models are developed to solve the concern of spatial dependence and heterogeneity in spatial data such as property market. Although various studies were conducted to control the influence of spatial dependence in property pricing, the bulk of these studies are on housing markets (Dziauddin et al., 2014; Montero-Lorenzo et al., 2009; Osland, 2010; Özyurt, 2013). To date, fewer studies have been conducted to explicitly control the influence of spatial dependence in commercial property pricing with divergent findings (Chegut et al., 2015; Ke et al., 2017; Kim & Zhang, 2005; Liang et al., 2017; Nappi-Choulet & Maury, 2009; Seo, Salon, Kuby, et al., 2018; Tu et al., 2004; Xu et al., 2016; Zhang et al., 2015).

The study of Tu et al. (2004) appears to be the first study to control the spatial and temporal dependences in the commercial property market using spatial econometrics. Using the Spatio-temporal Autoregressive (STAR) model, adopted from the housing study of Pace, Barry, Gilley, & Sirmans (2000), they found significant and substantial spatial and temporal dependence in Singapore office market price. Nappi-Choulet & Maury (2009), using a similar methodology, also found significant spatial and temporal dependence in Paris office prices. Ke et al. (2017) also found significant spatial dependence in Central London office market prices. Zhang et al. (2015) estimated commercial property prices for mass appraisal in Shenzhen, China using Spatial Error Model (SEM) and found significant spatial heterogeneity in the commercial property market associated with omitted neighbourhood variables as indicated by significant lambda (λ) value of 0.0850. Liang et al. (2017) also found significant spatial dependence affecting Melbourne office prices.

The study of Chegut et al. (2015) provided a broader coverage of the commercial property market by accounting for spatial and temporal dependence in six established global commercial property markets (Los Angeles, London, Hong Kong, Tokyo, Paris, and New York). The result shows divergent findings across the markets. While spatial dependence was significant in New York, London, Tokyo and Paris commercial property markets, no significant spatial dependence was found in Hong Kong and Los Angeles markets. The lack of spatial dependence in the Hong Kong and Los Angeles markets may be due to the homogenous commercial property market. However, Ke et al. (2017) found significant spatial dependence in commercial property prices even after accounting for market segmentation using submarkets dummy.

SPATIAL ECONOMETRIC MODELS IN COMMERCIAL PROPERTY LOCATION MODELLING

Spatial econometrics is an improved econometric model that is developed to address the issues and failure of Ordinary Least Squares regression hedonic price modelling when dealing with spatial data to adequately account for spatial location effect (Yang, Wang, Zhou, & Wang, 2018). The HPM provides the basis for the application of spatial econometrics. Spatial data are characterised by spatial heterogeneity and autocorrelation (Meen, 2016; Noh, 2019). The major spatial econometric models are the Spatial Lag Model (SLM), Spatial Error Model (SEM) and Spatial Durbin Model (SDM). The choice of a particular model depends on the nature of spatial autocorrelation. These methods have been applied to model the commercial property market spatially and explicitly.

The spatial lag model is used to model the influence of neighbouring commercial property prices on the price of subject commercial property (Droj & Droj, 2015; Özyurt, 2014). The SLM lags the dependent variable by adding a spatially weighted matrix to the spatially lagged variable to modulate the spatial correlation between the property variables and their neighbours. The studies that model location explicitly using spatial lag model include that of Özyurt (2013, 2014), who modelled the commercial property market including retail, office and industrial properties in Netherland, found significant spatial dependence. The respective studies found that the spatial lag model improves modelling accuracy above the traditional hedonic price model. Other studies that utilised the spatial lag model in modelling commercial property market spatially include Chegut et al. (2015, 2013), Ke et al. (2017), Liang et al. (2017), Nappi-Choulet & Maury (2009) and Tu et al. (2004). The studies found significant spatial dependence in office market accounting for which significantly improved accuracy of commercial property price prediction.

The Spatial Error Model (SEM), on the other hand, is used to control the influence of spatial autocorrelation in modelling regional data. SEM models how the residuals are spatially correlated. The spatial error model is also based on the premise that spatial autocorrelation is generated by omitting key neighbourhood variables that are not observed (Yu, Zhang, et al., 2017). Thus, instead of lagging the dependent variable, the model incorporates the spatial effects in the error terms (Yang et al., 2018). The spatial error model has been used to model the commercial property market. The study of Seo et al. (2019) found a significant correlation in the error terms. Another study that used a spatial error model is Zhang, Du, Geng, Liu, & Huang (2015) who modelled the commercial property market for mass appraisal in Shenzhen, China, and found significant spatial heterogeneity. Accounting for the spatial effect in these models significantly improved the commercial property market modelling.

The Spatial Durbin Model (SDM), adds a spatial lag to the property price to control the dependence of property prices on the neighbouring property prices and another spatial lag to the error term to control the spatial autocorrelation in the error terms (Li et al., 2015; Noh, 2019). Although the SDM has been applied in the residential property market and was found to significantly improve property price prediction accuracy (Li et al., 2015; Osland, 2010), there appears to be no evidence of its usage in modelling commercial property market.

CONCLUSION

Location is regarded as one of the most critical influencers of property prices. The popularised real estate parlance – Location, Location, Location – is a pointer of importance attached to the location in property pricing. The influence of location is more in the commercial property market. It is modelled traditionally using the conventional HPM by either controlling the neighbourhood effect using location dummies and by a relative distance of the subject property relative to other important landmarks. This implicit modelling of property location do not account for the spatial interactions inherent in the commercial property market. Such spatial interactions lead to spatial autocorrelation and heterogeneity. The error terms are spatially correlated against the Ordinary Least Squares (OLS) assumption of uncorrelated error terms and constant variance. The deficiency of the traditional method to account for the spatial effect leads to the estimated coefficients being bias, inconsistent and distorted. The spatial econometric techniques are developed to explicitly account for the location effect in property modelling by controlling spatial autocorrelation. Empirical researches show a superior performance of the spatial econometric models over the conventional hedonic pricing modelling in modelling location. However, despite this improved performance, the spatial econometric approach in modelling commercial property is rather minimal. This may not be unconnected with the general nature of the commercial property market lack of transaction data relative to other property classes. Accordingly, this paper reviewed the application of the spatial econometric models used in modelling the commercial property market. The review found that the spatial lag model has been applied in the commercial property market and found significant spatial dependence accounting, which improved the model's performance. The spatial error model was also found to enhance the performance of commercial property market modelling. However, the review does not found evidence of the application of SDM in the commercial property market even though the model was found very effective in housing market modelling. The review also found most of the studies that used spatial econometrics to be limited to the office submarket of the commercial property market. Thus, the paper recommends the application of spatial econometric models in modelling the commercial property market more especially the retail submarket. Similarly, the paper recommends the exploration of SDM in the commercial property market in future studies.

ACKNOWLEDGEMENTS

The authors would like to thank the Ministry of Education Malaysia for supporting this research under the Fundamental Research Grant Scheme Vot No. FRGS/1/2018/SS08/UTHM/02/1 and partially sponsored by Universiti Tun Hussein Onn Malaysia.

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.

Aliyu, B. A., Sani, H., Usman, H., & Muhammad, H. (2018). Ranking the Causative Factors of Mortgage Valuation Inaccuracy in Kaduna Metroplois. *Real Estate Management and Valuation*, *26*(3). https://doi.org/10.2478/remav-2018-0026

Alonso, W. (1964). *Location and Land Use. Toward a General Theory of Land Rent*. Cambridge: Harward University Press. https://doi.org/http://dx.doi.org/10.4159/harvard.9780674730854

Anselin, L. (2010). Thirty years of spatial econometrics. *Papers in Regional Science*, *89*(1). https://doi.org/10.1111/j.1435-5957.2010.00279.x

Bawuro, F. A., Shamsuddin, A., Wahab, E., & Usman, H. (2019). Mediating role of meaningful work in the relationship between intrinsic motivation and innovative work behaviour. *International Journal of Scientific and Technology Research*, *8*(9), 2076–2084.

Beracha, E., Hardin III, W. G., & Skiba, H. M. (2018). Real Estate Market Segmentation : Hotels as Exemplar. *Real Estate Finance Economics*, *56*, 252–273. https://doi.org/10.1007/s11146-017-9598-z

Bhattacharya, N., Lamond, J., Proverbs, D., & Hammond, F. (2013). Development of conceptual framework for understanding vulnerability of commercial property values towards flooding. *International Journal of Disaster Resilience in the Built Environment*, *4*(3), 334–351.

Bujanda, A., & Fullerton Jr., T. M. (2018). Infrastructure Impacts on Commercial Property Values Across El Paso in 2013. *Border Region Modeling Project*, *55*.

Can, A. (1992). Specification and estimation of hedonic housing price models. *Regional Science and Urban Economics*, *22*, 453–474.

Chegut, A. M., Eichholtz, P. M. A., & Rodrigues, P. J. M. (2015). Spatial Dependence in International Office Markets. *Journal of Real Estate Finance and Economics*, *51*(2), 317–350. https://doi.org/10.1007/s11146-014-9484-x

Chegut, A. M., Eichholtz, P., & Rodrigues, P. (2013). Transaction Based London Commercial Property Indices. *The Journal of Real Estate Finance and Economics, 47(4), 588-616*, *47*(4), 588–616.

Chiang, S. H. (2016). Interaction among real estate properties in China using three submarket panels. *Habitat International*, *53*, 243–253. https://doi.org/10.1016/j.habitatint.2015.11.038

Chiarazzo, V., dell'Olio, L., Ibeas, Á., & Ottomanelli, M. (2014). Modeling the Effects of Environmental Impacts and Accessibility on Real Estate Prices in Industrial Cities. *Procedia - Social and Behavioral Sciences*, *111*(February), 460–469.

https://doi.org/10.1016/j.sbspro.2014.01.079

Corgel, J. B., Liu, C. H., & White, R. M. (2015). Determinants of Hotel Property Prices. Retrieved May 17, 2019, from http://scholarship.sha.cornell.edu/articles/1012

Droj, L., & Droj, G. (2015). Usage of location analysis software in the evaluation of commercial real estate properties. In *Procedia Economics and Finance 32*, 826–832. https://doi.org/10.1016/S2212-5671(15)01525-7

Dziauddin, M. F., Powe, N. A., & Alvanides, S. (2014). Estimating the Effects of Light Rail Transit (LRT) System on Residential Property Values Using Geographically Weighted Regression (GWR). *Applied Spatial Analysis*. https://doi.org/10.1007/s12061-014-9117-z

Hardin III, W. G., Jiang, X., & Wu, Z. (2017). Inflation Illusion, Expertise and Commercial Real Estate. *Journal of Real Estate Finance and Economics*, *55*(3), 345–369.

Hayunga, D. K., & Pace, R. K. (2010). Spatial statistics applied to commercial real estate. *Journal of Real Estate Finance and Economics*, *41*(2), 103–125. https://doi.org/10.1007/s11146-009-9190-2

Ibeas, Á., Cordera, R., Dell'Olio, L., Coppola, P., & Dominguez, A. (2012). Modelling transport and real-estate values interactions in urban systems. *Journal of Transport Geography*, *24*, 370–382. https://doi.org/10.1016/j.jtrangeo.2012.04.012

Jeong, S., & Kim, J. (2011). A Study of Retail Property Prices in Seoul. In *ERES Conference 2011*.

Ke, Q., Sieracki, K., & White, M. (2017). A Spatial Analysis of the Central London Office Market. In *24th Annual European Real Estate Society Conference.* (pp. 1–16). Netherlands.

Kim, C. W., Phipps, T. T., & Anselin, L. (2003). Measuring the benefits of air quality improvement : a spatial hedonic approach. *Journal of Environmental Economics and Management 45*, *45*, 24–39.

Kim, J., & Zhang, M. (2005). Determining transit's impact on Seoul commercial land values: an application of spatial econometrics. *International Real Estate Review*, *8*(1), 1–26.

Li, W., Joh, K., Lee, C., Kim, J., Park, H., & Woo, A. (2015). Assessing Benefits of Neighborhood Walkability to Single-Family Property Values : A Spatial Hedonic Study in Austin , Texas. *Journal of Planning Education and Research*. https://doi.org/10.1177/0739456X15591055

Li, Y., He, L., Xu, W., Wang, H., & He, Z. (2013). Using GIS and hedonic in the modelling of spatial variation of housing price in Xiamen city. *International Review for Spatial Planning and Sustainable Development*, *1*(4), 29–42. https://doi.org/10.14246/irspsd.1.4_29

Liang, J., Reed, R., & Crabb, T. (2017). The contribution of spatial dependency to office building price index: A melbourne case study. *Journal of Property Investment & Finance*.

Meen, G. (2016). Spatial housing economics : A survey. *Urban Studies*, *53*(10), 1987–2003. https://doi.org/10.1177/0042098016642962

Montero-Lorenzo, J.-M., Larraz-Iribas, B., & Paez, A. (2009). Estimating commercial property prices : an application of cokriging with housing prices as ancillary information. *J Geogr Syst*, *11*, 407–425. https://doi.org/10.1007/s10109-009-0095-7

Muth, R. F. (1969). *Cities and Housing: The Spatial Pattern of Urban Residential Land Use*. Chicago & London: The University of Chicago Press.

Nappi-Choulet, I., & Maury, T.-P. (2009). A Spatiotemporal Autoregressive Price Index for the Paris Office Property Market. *Real Estate Economics*, *37*(2), 305–340.

Noh, Y. (2019). Landscape and Urban Planning Does converting abandoned railways to greenways impact neighboring housing prices ? *Landscape and Urban Planning*, *183*(September 2017), 157–166. https://doi.org/10.1016/j.landurbplan.2018.11.002

Orford, S. (2017). *Valuing the Built Environment: GIS and House Price Analysis*. New York: Routledge Taylor & Francis group.

Osland, L. (2010). An Application of Spatial Econometrics in Relation to Hedonic House Price. *JRER*, *32*(3).

Özyurt, S. (2013). *Does the spatially augmented transaction-based commercial property price indicator perform better than the standard one ? Evidence from micro data* (Graduate Programme Research Paper 2012-2013 No. Graduate Programme Research Paper 2012-2013).

Özyurt, S. (2014). *Spatial dependence in commercial property prices: micro evidence from the Netherlands* (ECB Working Paper No. 1627). Frankfurt.

Pace, R. K., Barry, R., Gilley, O. W., & Sirmans, C. F. (2000). A method for spatial – temporal forecasting with an application to real estate prices. *International Journal of Forecasting*, *16*(2), 229-246.

Pace, R. K., Barry, R., & Sirmans, C. F. (1998). Spatial Statistics and Real Estate. *Journal of Real Estate Finance and Economics*, *17*(1), 5–13.

Raposo, I. G., & Evangelista, R. (2017). A transactions-based commercial property price index for Portugal. *Financial Stability Papers*, *3*(March), 1–25.

Seo, K., Salon, D., Kuby, M., & Golub, A. (2018). Hedonic modeling of commercial property values : distance decay from the links and nodes of rail and highway infrastructure Hedonic modeling of commercial property values : distance decay from the links and nodes of rail. *Transportation*, (March). https://doi.org/10.1007/s11116-018-9861-z

Seo, K., Salon, D., Kuby, M., & Golub, A. (2019). Hedonic modeling of commercial property values : distance decay from the links and nodes of rail and highway infrastructure. *Transportation*, *46*(3), 859–882. https://doi.org/10.1007/s11116-018-9861-z

Tobler, W. R. (1970). A Computer Movie Simulating Urban Growth in the Detroit Region. *Economic Geography*, *46*(sup1), 234–240. https://doi.org/10.1126/science.ns-13.332.462

Tu, Y., Yu, S., & Sun, H. (2004a). Transaction-Based Office Price Indexes : A Spatiotemporal Modeling Approach. *Real Estate Economics*, *32*(2), 297–328.

Tu, Y., Yu, S., & Sun, H. (2004b). Transaction-based office price indexes: a spatiotemporal modeling approach. *Real Estate Economics*, *32*(2), 297–328.

Usman, H., & Lizam, M. (2020). Empirical Modelling of Commercial Property Market Location Submarket using Hedonic Price Model in Malaysia. In *Proceedings of the 5th NA International Conference on Industrial Engineering and Operations Management*. Detroit, Michigan, USA, August 10 - 14, 2020.

Usman, H., Lizam, M., & Adekunle, M. U. (2020). Property price modelling, market segmentation and submarket classifications: A review. *Real Estate Management and*

Valuation, *28*(3), 24–35.

Usman, H., Lizam, M., & Burhan, B. (2020a). A Review of Property Attributes Influence in Hedonic Pricing Model. In *Proceedings of the 2nd African International Conference on Industrial Engineering and Operations Management* (pp. 2795–2805). Harare.

Usman, H., Lizam, M., & Burhan, B. (2020b). Review of Issues in the Conventional Hedonic Property Pricing Model. In *Proceedings of the 2nd African International Conference on Industrial Engineering and Operations Management* (pp. 2806–2816). Harare.

Usman, H., Lizam, M., & Burhan, B. (2021). A priori spatial segmentation of commercial property market using hedonic price modelling. *Real Estate Management and Valuation*, *29*(2), 16–28.

Wiley, J. A. (2017). Leverage, liquidity and information in commercial property prices. *Journal of Property Research*, *34*(2), 77–107. https://doi.org/10.1080/09599916.2017.1320683

Wyatt, P. J. (2010). The development of a GIS- based property information system for real estate valuation. *International Journal of Geographical Information Science*, *11*(5), 37–41. https://doi.org/10.1080/136588197242248

Xu, T., Zhang, M., & Aditjandra, P. T. (2016). The impact of urban rail transit on commercial property value: New evidence from Wuhan , China. *Trasportation Research Part A*, *91*, 223–235.

Yang, L., Wang, B., Zhou, J., & Wang, X. (2018). Transportation Research Part D Walking accessibility and property prices. *Transportation Research Part D*, *62*, 551–562. https://doi.org/10.1016/j.trd.2018.04.001

Yu, H., Pang, H., & Zhang, M. (2017). Value-added effects of transit-oriented development : The impact of urban rail on commercial property values with consideration of spatial heterogeneity : Rail transit and commercial ... Value-added effects of transit-oriented development : The impact of. *Papers in Regional Science*, 1–23. https://doi.org/10.1111/pirs.12304

Yu, H., Zhang, M., & Pang, H. (2017). Evaluation of transit proximity effects on residential land prices : an empirical study in Austin , Texas. *Transportation Planning and Technology*, (8), 1–14. https://doi.org/10.1080/03081060.2017.1355880

Zhang, R., Du, Q., Geng, J., Liu, B., & Huang, Y. (2015a). An improved spatial error model for the mass appraisal of commercial real estate based on spatial analysis : Shenzhen as a case study. *Habitat International*, *46*, 196–205. https://doi.org/10.1016/j.habitatint.2014.12.001

Zhang, R., Du, Q., Geng, J., Liu, B., & Huang, Y. (2015b). An improved spatial error model for the mass appraisal of commercial real estate based on spatial analysis : Shenzhen as a case study, *46*, 196–205.

Zhang, X., Zheng, Y., Sun, L., & Dai, Q. (2019). Urban Structure , Subway Systemand Housing Price : Evidence from Beijing and Hangzhou , China, 11–13. https://doi.org/10.3390/su11030669.

Received: 12th July 2021. Accepted: 7th Sept 2021