Spatial Autocorrelation and Real Estate Studies: A Literature Review

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Abstract

Spatial autocorrelation is a phenomenon where the values of a variable located within certain geographic area show a similar pattern. It is a source of imperfection in house price modelling that employs the popular technique of hedonic regression. Despite its long established concept, it is only recently when spatial autocorrelation has started to gain the attention of real estate studies. However, the evidence has come mainly from the USA. This paper reviews the literature on spatial autocorrelation and real estate studies. It describes some basic aspects of spatial autocorrelation in respect of hedonic price modelling (HPM) for housing markets. The importance of considering spatial autocorrelation and ways of dealing with the phenomenon are outlined. The paper also discusses two main approaches of modelling spatial autocorrelation, namely the spatial weight matrix and the geo-statistical approaches. It stresses the preference of the former in previous real estate studies that involve economic analysis. The paper concludes by highlighting the importance of considering spatial autocorrelation when cross sectional data are used. Evidence from countries including Malaysia would enrich the literature of spatial autocorrelation consideration in real estate studies.

Keywords: spatial autocorrelation, house price modelling, hedonic technique, spatial statistics

1. Introduction

Real estate studies have shown that house price hedonic modelling is popular for housing market analysis. House price hedonic modelling involves a regression of three main property characteristics namely structural, accessibility and neighbourhood. The involvement of many variables that represent these property characteristics can induce hedonic problems of multicollinearity, spatial autocorrelation and heteroscedasticity. Of these, spatial autocorrelation has received the least attention in the real estate literature (Suriatini, 2005). According to Des Rosiers et al. (2000) spatial autocorrelation is one of the hedonic problems that can cause imperfections to its application in housing market analysis. Hence, it is important to consider the phenomenon in hedonic price modelling (Malpezzi, 2003).

Unlike serial (or time series) correlation, spatial autocorrelation is less common in real estate research. This is not surprising because, compared to the former, the latter is more complex and not straightforward. Time is one-dimensional and the direction of correlation will be backwards in time, the only question being how far. Meanwhile, spatial correlation occurs in two dimensions and no particular direction is ruled out a priori (Bailey and Gatrell, 1995, 4). This indicates the complexity of spatial autocorrelation.

Before spatial autocorrelation and house price hedonic modelling is discussed, an understanding of its basic concepts is imperative. Thus, the next section describes spatial autocorrelation in terms of its meaning, causes and types. This is followed by a discussion on the importance of considering spatial autocorrelation in hedonic modelling as well as the approaches that can be adopted in dealing with the phenomenon. The paper concludes by highlighting the need to carry out more research that considers spatial autocorrelation when cross sectional data are used.

2. Meaning, Causes And Types Of Spatial Autocorrelation

Literally speaking, the "spatial" term of the "spatial autocorrelation" phrase refers to a geographical dependence structure for observations. The term "correlation" refers to a relationship between entities, and the prefix "auto" refers to the fact that a single variable is being related to itself (Griffith, 1984, 10). Several formal definitions of spatial autocorrelation are offered by Griffith (1992), Anselin and Bera (1998) as well as Heppel (2000) as follows:

[…] may be defined as a measure of true but masked information content in geo-referenced data (Griffith, 1992, 273).

[…] is the coincidence of value similarity with locational similarity (Anselin and Bera, 1998, 241).

[…] is the presence of spatial pattern in a mapped variable due to geographical proximity (Heppel , 2000, 775).

While Griffith (1992) focuses on the disclosure of some hidden information by a spatial autocorrelation measure, the other two authors stress two common elements of variable attribute and location characteristic.

The measures of spatial autocorrelation indicate an average correlation between observations based upon replicated realisations of the geographic distribution of some attribute (Griffith 1992, 278). In other words, spatial autocorrelation is a phenomenon where values of a variable show regular pattern over space (Odland, 1988 in Hamid, 2002). According to Anselin and Bera (1998, 241), a crucial issue in the definition of spatial autocorrelation is the notion of "locational similarity", or the determination of those locations for which the values of the random variable are correlated. Such locations are referred to as "neighbours". In real estate research, spatial autocorrelation is studied for the statistical improvements that can be gained in hedonic modelling (Carter and Haloupek, 2000). Accordingly, in the context of this paper, spatial autocorrelation refers to a situation where the Ordinary Least Squares (OLS) residuals[1] exhibit a regular pattern over space. The following texts discuss the causes and types of spatial autocorrelation.

2.1 Causes of spatial autocorrelation

Spatial autocorrelation arises in cross-sectional data whereby the correlation occurs in units that are the same or among contiguous units (Hamid, 2002). Legendre (1993) states that two sources of spatial autocorrelation in data are the physical forcing of environmental variables and community processes. Based on Dunse et al. (1998), Basu and Thibodeau (1998), Bowen et al. (2001), Gillen et al. (2001) and Tu et al. (2004), there are at least three sources of spatial autocorrelation, namely, the property characteristics, the property price determination process and mis-specification of the OLS model. These are discussed as follows.

Regarding the **property characteristics**, firstly, properties in close proximity tend to have similar structural characteristics - such as square feet of building or living area, dwelling age and design features. Tu et al. (2004) refer these as the building quality. The similar quality of the building is a natural consequence of the fact that proximate properties tend to be developed at the same time (Gillen et al., 2001). This is particularly relevant in discussing the remarkable occurrence of spatial autocorrelation in the models related to high-rise properties. Secondly, apart from having properties of potentially similar structural characteristics, and hence, building quality, residents in the same neighbourhood may follow similar commuting patterns (Gillen et al., 2001), suggesting similar accessibility conditions. Thirdly, according to Basu and Thibodeau (1998) and Gillen et al. (2001), one reason house prices may be spatially autocorrelated is that property values in the same neighbourhood capitalise shared location amenities. This is true when properties within the same neighbourhood share important neighbourhood amenities (for example, neighbourhood properties have access to the same public schools or the nearest shopping centre). This implies that it is also important to include hedonic variables that can capture the effects of neighbourhood amenities on price in modelling the housing markets.

[1] In hedonic regression, the OLS residual is the difference between the observed and the predicted price. The observed prices are the transacted prices as agreed between a willing buyer and a willing seller and available to the analysts. The predicted prices are prices obtained using the model estimated in the hedonic regression. A positive residual indicates underpricing or underestimation. A negative residual indicates overpricing or overestimation.

Spatial autocorrelation can also arise out of the price determination or **valuation process.** Potential buyers and sellers may appoint a real estate professional to assess the open market value of the properties in question as well as having their own estimated values based on knowledge of the surrounding area. When the price is determined by a real estate professional, the roles of local housing market trends and condition likely plays a more formal role (Bowen et al., 2001). Thus, there may be market inertia due to the processes that influence the determination of property values in one location connecting the values in different places (Dunse et al., 1998). For example, valuations of individual properties in spatially separated markets may be inter-linked by similar personnel undertaking the valuation process. This can give rise to the incidence of spatial autocorrelation among the properties valued by the same estate agent, for example, as in the case of Can (1990).

Apart from the property characteristics and the process of price determination, mis-specification may also be a source of spatial autocorrelation (Dunse et al., 1998). **Mis-specification** arises when the model has missing important variables, extra unimportant variables, and/or uses an unsuitable functional form. The functional form used is unsuitable when the non-linear effect of certain property characteristics on price is not sufficiently captured or not captured at all. This is not uncommon because as while property is complex, there is no specific theory for hedonic regression to follow regarding the variables to use and the correct specification to employ in the model estimation (Suriatini, 2005).

The occurrence of spatial autocorrelation can be more complex for multi-unit property such as high-rise flats and condominiums. Citing Sun et al. (2004), Tu et al. (2004) argue,

In the multiunit residential housing market, the causes of spatial autocorrelation are complicated by both building and neighbourhood effects. The spatial interdependence among the properties within one building is different from the one among the properties in the neighbourhood (Tu et al., 2004, 300).

In their studies that involve both time series and cross sectional data, Tu et al. (2004) point out that the inaccuracy in using proxies to measure the property characteristics and location effects generates spatial autocorrelations among hedonic residuals. Thus, it is noted that the sources of spatial autocorrelation also stem from the structural and location characteristics of properties, and the problem may be more complicated in properties such as flats than in other single unit properties such as detached properties.

2.2 Types of spatial autocorrelation

The occurrence of spatial autocorrelation can be examined in at least three forms: of positive or negative, spatial lag or spatial error, and isotropic or anisotropic. These are discussed as follows.

2.2.1 Positive or negative

According to Lee and Wong (2001, 148), positive autocorrelation is said to occur when high or low values for a random variable tend to cluster in space. Negative autocorrelation occurs when locations tend to be surrounded by neighbours with very dissimilar values. Of the two types, the former is by far the more intuitive. One example for positive spatial autocorrelation is where similar values for a variable (such as OLS residuals of hedonic models) tend to cluster together in adjacent observations.

The existence of positive spatial autocorrelation implies that a sample contains less information than an uncorrelated counterpart. In order to carry out statistical inference properly, this loss of information must be explicitly acknowledged in estimation and diagnostic tests. This is the essence of the problem of spatial autocorrelation in applied econometrics (Anselin and Bera, 1998, 241). The importance lies in the fact that its existence violates the assumption of uncorrelated error terms in model estimation (Can, 1990).

2.2.2 Spatial error dependence or spatial lag dependence

In the context of hedonic modelling, spatial autocorrelation concerns the spatial correlation of the error terms and can take two forms (which may occur jointly) namely, spatial error dependence and spatial lag dependence (Patton and McErlean, 2003).

Spatial error dependence refers to the assumption of correlated errors as occur among the independent variables. It can arise from the spatial correlation between non-observable explanatory (or latent variables) (LeSage, 1997), or omitted variables (Wilhelmsson, 2002a) such as noise and pollution common among all of the observations. Several houses in the same neighbourhood might also be subject to the same common externality which is unmeasured. Spatial error dependence can also result from variables measurement error or mis-specification of the functional form (Wilhelmsson, 2002a). A common source of measurement error is the phenomenon of ecological fallacy, where data of higher aggregation level such as the census based data is used to represent the individual observation such as a single property location. The result is a spatially correlated error structure caused by the spillover effects of measurement errors, which can lead to inefficient although unbiased estimation of the parameters.

Spatial lag dependence refers to the assumption of correlated errors as occur between the dependent variables. In this study, it may involve distance from other house price observations. It can arise because of spatial spillover effects between observations of the dependent variable (Saavedra, 2003), such as the impact of the price of one housing unit on the price of its neighbours (Wilhelmsson, 2002a). Patton and McErleans (2003) contend that the consequences of ignoring spatial lag dependence are more severe than the consequences of ignoring spatial error dependence. The reason is that the former is related to theoretical considerations while the latter is related to statistical one (LeSage, 1997). Thus, inference for housing markets based on OLS models suffering spatial lag dependence can be more questionable than the one that suffers spatial error dependence.

2.2.3 Isotropic or anisotropic

Isotropic spatial autocorrelation is said to occur when the autocorrelation is a function of direction. Anisotropic spatial autocorrelation occurs when the occurrence is a function of both the distance and the direction separating points in space. Isotropic spatial autocorrelation usually declines with distance (Pace and Barry, 1997). This is based on the *first law of geography* by Tobler (1970) that data that are more closely together are more correlated than those that are far apart (Cressie, 1989). As for anisotropic, there is no a priori principle as to the prevailing direction. Thus, the latter is more complicated than the former to deal with.

Most research on spatial autocorrelation in house price has assumed isotropy. Nevertheless several authors such as Gillen *et al*. (2001) analyse whether the hedonic residuals are anisotropic rather than isotropic. Their empirical results suggest that the hedonic residuals are spatially autocorrelated in both distance and direction. Besner (2002) also consider anisotropy while Gelfand *et al.* (2004) acknowledge the relevance of other types of spatial autocorrelation than isotropic in real estate studies. Beyond real estate studies, Molina and Feito (2002) who realise the limited availability of techniques to analysing anisotropy have proposed a computer-graphic-based method of analysis referred to as second-order bivariate circular statistics. According to them, the method allows the identification of the existence of anisotropy in digital images and the quantification of the direction in which it appears. No application of this is evident in real estate studies. Given that the potential technique for dealing with anisotropy is still an under-developed topic and a more difficult modelling problem than isotropy (Pace *et al*., 1998a) it has not been not dealt with in the study by Suriatini (2005).

3. The Importance Of Considering Spatial Autocorrelation In Hedonic Price Modelling

According to Miron (1984), the effect of spatial dependence among the unobserved error term is twofold. First, it makes OLS estimates of the t-test values unreliable. In other words, the t-values no longer tell accurately whether the included explanatory variables have a significant effect on the average house price. Secondly, it is no longer true that OLS estimates are relatively efficient, that is having small sampling variability associated with them (Miron, 1984, 205). The importance of these statistical elements in a hedonic price modelling substantiates the need to detect the existence of spatial autocorrelation in OLS residuals. This is due to the fact that spatial autocorrelation in sample data can alter the conclusions of statistical analyses performed without due allowance for the former. The existence of spatial autocorrelation does not provide minimum-variance unbiased linear estimators and produces a bias in the estimation of correlation coefficients and variances (Dutilleul *et al*., 1993).

In practice, it is important to detect the existence of spatial autocorrelation in the OLS residuals. This is to help the judgement of the reliability of the hypothesis testing based on the model. In addition, Wiltshaw (1996) stresses that the importance of considering spatial autocorrelation applies to every cross-sectional empirical study of OLS. According to him, no particular case study whether imagined or real, can confirm the presence or absence of spatial autocorrelation in other market analyses. Each case must be analysed separately, just as done when testing for temporal autocorrelation, heteroscedasticity and other hedonic problems. According to Overmars et al. (2003), if autocorrelation is detected on the regression residuals, this can imply that the regression model should have an autoregressive structure, or that non-linear relationships between the dependent and the independent variable are present, or that one or more important regressor variables are missing.

In the study by Wilhelmsson (2002a), the Moran's I test shows that real estate data is highly spatially dependent. Thus, he believes that even if one tries to account for spatial effects with the inclusion of distance and sub-markets dummies, one cannot reject the hypothesis of no spatial autocorrelation. The existence of spatial autocorrelation despite detailed hedonic specifications is evident in Harrison and Rubinfeld (1978) as well as Des Rosiers *et al.* (2001).

Ignoring spatial autococorrelation leads to serious violations of the underlying independence assumption of OLS regression (Paez et al., 2001), which can result in erroneous statistical inference due to loss of much predictive power (Pace and Barry, 1997). The importance of detecting its existence as indicated by Bowen *et al.* (2001) is appealing. They state that

……. without explicit investigation, the analyst has no way of knowing if there is a violation, and if so, where the violation implications lie along the "subtle-to-severe" continuum (Bowen et al., 2001, 472-473).

This statement supports Wiltshaw (1996) in that spatial autocorrelation is more an empirical issue than a theoretical one and, hence, should be tested in every case of cross sectional analysis.

According to Anselin (1998), the presence of spatial dependence in cross sectional geo-referenced data can be considered a nuisance or a substantive. He elaborates that it is a nuisance if the focus of analysis is on obtaining proper statistical inference (such as of estimation, hypotheses testing and prediction). Meanwhile, it is a substantive if the focus of analysis is on discovering the form of spatial interaction such as the precise nature of spatial spillover, and the economic and social processes that lie behind it.

When spatial dependence is considered a nuisance, the main objective is to correct statistical procedures for the effect of the spatial autocorrelation, for example by increasing the sample size or by using robust methods or adjustments that incorporates the spatial autocorrelation in a regression error term. When it is a substantive, the main objective is to incorporate the structure of spatial dependence into a statistical model and how to estimate and interpret it. Anselin (1998) believes that the prevalence of spatial dependence in the cross-sectional data used in real estate analysis requires the application of appropriate techniques of spatial statistics and spatial econometrics for efficient estimation, valid inference and optimal prediction (Pace and LeSage., 2003).

Des Rosiers and Theriault (1992) believe that the identification and interpretation of complex phenomena such as spatial autocorrelation of hedonic models residuals would simply not be feasible without the help of a Geographical Information System GIS. Nevertheless, Hamid (2002) suggests two options for detecting spatial autocorrelation: 1) Estimate regression prediction errors and input these estimates to GIS data file for spatial display; 2) Use spatial correlation statistics such as Moran's I. Figueroa (1999) also recognises the benefits that GIS and spatial statistics such as Moran's I can give to the analysis of OLS residuals for spatial autocorrelation. GIS can indicate whether spatial autocorrelation exists while Moran's I can formally test the degree of spatial autocorrelation. The study by Suriatini (2005) employs both GIS and spatial statistics. It suggests that spatial statistics can complement GIS and is specifically helpful in that the former is able to not only detect but also specify spatial autocorrelation explicitly. Hence, the following section focuses on the use of spatial statistics[2] in dealing with spatial autocorrelation in real estate.

4. Dealing With Spatial Autocorrelation

Dealing with spatial autocorrelation can involve its formal testing and explicit modelling. These are discussed as follows.

4.1 Formal testing of spatial autocorrelation

Spatial autocorrelation analysis involves analysing the degree to which the value of a variable for each location co-varies with values of that variable at contiguous or nearby locations (Flahaut et al., 2003). Several formal tests are available for this. Moran's I, Geary's C, the joint count and Gi(d) have been developed as descriptive statistics to measure spatial autocorrelation (Anselin and Bera, 1998, 264). Lagrange Multiplier (LM), Likelihood ratio (LR) and Wald (W) are designed as specification tests for the diagnostics of spatial autocorrelation (Kim, 1997). Nonetheless, Moran's I and LM seem more popular in previous studies. For example, Theriault et al. (2003) use Moran's I while Day (2003) uses LM.

Bell and Bockstael (2000) note that there are two types of diagnostic tests for LM, namely LM (error) for spatial error dependence and LM (sar) for substantive dependence. They highlight that tests for spatial effects have difficulty discerning between the two sources of

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[2] Spatial statistics consider spatial dependencies to provide inference that is more realistic, better prediction and more efficient parameter estimation (Pace et al, 1998). Spatial statistics is concerned with the methods of analysis that explicitly consider the spatial arrangement of the data (Martinez and Martinez, 2002, 465) and are appropriate tools for analysing spatial autocorrelation. They are the most useful tools for describing and analysing how various geographic objects (or events) occur or change across the study area (Lee and Wong, 2001, 132).

Typically, methods in spatial statistics fall into one of three categories that are based on the type of spatial data that is being analysed. These types of data are called: point pattern data , geostatistical data and lattice data (Martinez and Martinez, 2002, 466-467). However, the distinguishing feature of the different types of data can be somewhat confusing. Notwithstanding, real estate data can be treated as geostatistical data or lattice data. Nevertheless, Anselin and Bera (1998, 240) suggest that lattice is more appropriate for economic data (which include real estate data) since it is to some extent an extension of the ordering of the observations on a one-dimensional time axis to an ordering in a two-dimensional space. Therefore, house price data can be treated as lattice data. Wilhelmsson (2002a), Berg (2005), Brasington and Hite (2005) and Suriatini (2005) also treat the data in their studies this way. This brings the discussion to how to deal with spatial autocorrelation.

spatial dependence as mentioned earlier. According to Bell and Bockstael (2000) those that have been designed to test against one form still have some power against the other. Therefore, even if only one form exists, bothtypes of tests may yield significant results. Can (1996) and Bell and Bockstael (2000) note that, if both tests are significant and have high values, the one with the highest value will tend to indicate the correct form of dependence. This guideline is adopted in Suriatini (2005) particularly in using the LM tests for detecting spatial autocorrelation of the hedonic models estimated.

4.2 Modelling spatial autocorrelation explicitly

Pace *et al*. (1998b) have suggested two ways for dealing with spatial data to make them fit the mould of the OLS. First is by modelling the coefficients for the independent variables correctly (β(X)). Second is by modelling the correlation in error explicitly (ε). This is consistent with Dutilleul et al. (1993). The following discussion is mainly based on Pace et al. (1998b).

4.2.1 Modelling β(X)

According to Pace et al. (1998b), spatial autocorrelation can be dealt with by specifying the independent variables in the hedonic model correctly, taking into account all the important factors and the nonlinearity so that the spatial dependency is removed (Dutilleul *et al*., 1993) and the residuals appear patternless over space. Responding to this assertion, modellers often add regressors to capture spatial effects such as distance to various centres, neighbourhood indicators, as well as spatially interactive variables (such as postcode area x number of room) and so forth to help specify β(X), that is, the parameters for independent variables. This shows that adding extra variables to deal with unmeasured spatial elements is one way of dealing with hedonic problems.

Nevertheless, one caveat to a strategy of adding new variables is that, as pointed out by Pace *et al*. (1998b) the number of variables needed to remove all local variation can quickly grow out of control. Too many variables will affect the models' degrees of freedom and thus the strength of the modelling (Valente *et al*., 2005). Apart from that, Pace *et al*. (1998) note that such models still do not usually yield patternless residuals over space. Supporting this, Besley *et al*. (1980, 239) reveal the spatial clustering of residual from the well known hedonic pricing study of Harrison and Rubinfeld (1978) despite the inclusion in the latter of two variables measuring distances and a neighbourhood indicator variable. Des Rosiers *et al*. (2001) also exhibit spatial autocorrelation despite the extensive hedonic specification that includes accessibility to various centres. This indicates that modelling the independent variables correctly is not an easy task because housing is a complex good and its characteristics can affect price in a nonlinear fashion (Meen and Meen, 2003; Ekeland *et al*., 2002; Ekeland *et al*., 2004; Goodman, 1998).

Another alternative for dealing with spatial autocorrelation is by modelling the correlated errors.

4.2.2 Modelling ε

Pace *et al*. (1998b) suggest that in dealing with spatial autocorrelation in hedonic modelling, one can also model the possible dependence of the true errors, that is, the correlated errors, ε. This is consistent with Dutilleul et al. (1993) who also suggest the use of statistical methods that can modify the variance estimation. Pace *et al*. (1998b) elaborate that the *n* by *n* covariance matrix, Ψ, expresses such a dependence where Ψij represents the covariance between any two errors, *i*th and *j*th errors. The magnitude of the covariance between any two errors εi and εj declines as distance (under some metric) increases between location *i* and location *j*.

The literature shows that the means of modelling the estimated covariance matrix or functions of the estimated covariance matrix distinguishes many of the strands of spatial statistics literature. Given an estimated variance-covariance matrix Ψ (with hat) one could compute an Estimated Generalised Least Squares (EGLS) as well as maximum likelihood (ML). However, Pace *et al*. (1998) warn that mis-specifying the variance-covariance matrix can result in loss of efficiency, loss of predictive accuracy and biased inference.

The following discussion focuses on two approaches of modelling the correlated errors as outlined by Suriatini (2005).

4.3 Two approaches of modelling ε

Explicit modelling of spatial autocorrelation can make use of spatial models (Cressie, 1989), which are generally specified as linear regression models with spatial interdependence taking the form of a linear additive relationship of observations on neighbours (Wilhelmsson, 2002a).

Supporting Legendre (1993), Dubin (2003) suggests that there are two main schools of thought concerning how the spatially autocorrelated error term in a regression can be modelled, namely, the geostatistical approach and the weight matrix approach.

4.3.1 Geostatistical approach

The geostatistical approach is also known as kriging[3] or raw data approach (Legendre, 1993). It is based on co-variance matrix (Kim *et al*., 2003). It postulates that the correlation between observations is a function of the distance separating their location. This function is known as a correlation function. However, Dubin (2003) notes that this is strictly true only for isotropic models.

Several other studies that apply the geostatistical approach include Dubin (1988, 1992, 1998), Basu and Thibodeau (1998) and Daud (1999). Dubin (1988, 1992, 1998) applies kriging to the estimation of the covariance structure in the model. Basu and Thibodeau (1998) carry out an empirical analysis using a semi-log house price hedonic equation and a spherical autocorrelation function. They find that in some sub-markets the residuals are spatial autocorrelated throughout the sub-markets and, in some others, residuals are spatial autocorrelated within 1,200 metres of each other.
Daud (1999) investigates the potential of kriging for mass appraisal. Comparing kriging with multiple regression analysis (MRA), he finds that the former does not outperform the latter and suggests further investigation on kriging. He concludes that,

Kriging should be useful where the concern is with the investigation on locational factors in isolation in valuation as opposed to the investigation of property values that involves a multiplicity of factors (Daud, 1999, 221).

With similar implication, Patton (2002) argues that the geostatistical approach is not suitable when the aim of the hedonic modelling is to explain economic behaviour. According to him, the geostatistical approach rests on strong assumptions concerning the stationarity of the residual[4] . Specifically, it is necessary to assume second order stationarity, that is, the mean and variance are constant (Dubin, 2003). This implies that the approach is not suitable in the presence of heteroscedasticity, that is when the variance is not constant. Moreover, as part of the geostatistical approach, Patton (2002) argues that it is necessary to exclude locational characteristics (eg. distance to CBD) from the hedonic model, so that the error terms solely pick up the influence of location factors. Consequently, the model suffers from missing variables, thereby invalidating the interpretation of the regression coefficients. Although he agrees that the geostatistical approach may be suitable for predictive purposes, he thinks that the process of excluding variables is at odds with the practice of explaining economic behaviour. Thus, Daud (1999) and Patton (2002) imply that the geostatistical approach is not a recommended approach to employ in a real estate study that involves explanation of the economic behaviour of the hedonic regressions.

4.3.2 Weight matrix approach

The weight matrix approach is also known as the lattice or the matrix approach (Legendre, 1993). Unlike the geostatistical approach, rather than using a function to model the correlations, the error generating process is modelled directly (Dubin, 2003). This approach uses a matrix, W, commonly known as a spatial weight matrix, or connectivity matrix, or spatial contiguity matrix. The matrix captures the spatial relationships (or connectivity) between all pairs of observations by defining *a priori* the strength of potential spatial dependence (Patton, 2002). Thus, spatial autocorrelation can be captured in the spatial lag or spatial error models based on proper definition of the weight matrices.

As its name suggests, a spatial weight matrix describes the contiguity relations between spatial units (Kim, 1997). So, spatial weight matrices are generated by a measure of the degree of contiguity, two main types of which may be expressed as the simple contiguity or the distance contiguity (Bowen *et al*., 2001) between two spatial units. **The simple contiguity** refers to a situation where, if two spatial units have a common border, they are assigned a value of "1" for a first order binary contiguity matrix. **The distance contiguity** can be of distance decay or distance binary (Patton, 2002). Patton (2002) implies that the simple contiguity is suitable for regional level data (such as census area) while for lower level data like individual location, the distance contiguity is more appropriate.

The spatial weight matrix, W, raises important issues. Anselin (1988, 1984) argues that the spatial weight matrix should be constructed by a spatial interaction theory such as the concept of accessibility, instead of simple physical feature of spatial units. However, there is no clear-cut agreement on the choice of a proper weight matrix. According to Dubin (2003), there is little agreement regarding the best form for the connectivity matrix and several forms are commonly used. All of these depend on the separation distance in some fashion; however, the specification also involves a parameter, the value of which is typically chosen by the researcher on an *a priori* basis and the weights are generally treated as exogeneous.

[3] Kriging is a linear method of spatial prediction (Cressie, 1989). It is a minimum mean squared error statistical procedure for spatial prediction that assigns a differential weight to observations that are spatially closer to the dependent variable's location. With ordinary kriging, the weights sum to one and are derived from the estimated semivariogram (Thibodeau, 2003).

[4] This is supported by Tse (2002).

Once the researcher has specified the weight matrix, the spatial autocorrelation parameter, normally denoted by lambda, λ, is estimated to complete the specification of the correlation matrix, K[5] .

Despite the absence of theoretical guidance, an injudicious selection of W may result in doubtful conclusions. Wiltshaw (1996) stresses that the implications for behaviour of the weights need to be carefully thought through; indeed it will probably be appropriate to experiment with alternative forms (Cliff *et.al*., 1981, 16-19). For example, Wilhelmsson (2002a) considers five alternatives[6] of weight matrix. He finds that the model with the inverse distance (within 600 metres) explains the variation in price best and the model with four nearest neighbours makes the worst explanation of the price variation.

4.4 Spatial weight matrix approach and real estate

Due to little theoretical justification underlying the choice of model, Dubin (2003) argues that the researchers never know which model has generated the error term. Given the lack of theoretical guidance, it is possible that the researcher is estimating a misspecified model (Dubin, 2003). In the study by Dubin (2003), the Monte Carlo evidence shows that with respect to prediction, the geostatistical models dominate the weight matrix models. However, the author admits that both methods have been used with some success in the literature (Dubin, 2003). While other researchers are more inclined to argue that one method is better than the other, Militino *et al*. (2004) attempt to combine both approaches in one model[7] .

Nonetheless, the empirical investigation by Suriatini (2005) focuses on the spatial weight matrix approach. This has been based on several studies including Lesage (2002) and Pace *et al*. (1998b) who imply its suitability for real estate research. Spatial models not only can model spatial autocorrelation but also can detect whether it is of spatial error or spatial lag dependence (or both). This is relevant with the second form of spatial autocorrelation mentioned earlier. A combination of both creates a model that considers both types of spatial autocorrelation.

A discussion on the spatial weight matrix approach of spatial models should include a specific mention of the two main types of models, spatial lag model, and spatial error model as reflected in the discussion above. Other studies that consider the spatial weight matrix approach include Can (1990, 1992), Can and Megbolugbe (1997), Bell and Bockstael (2000) and Brasington (1999). The discussion to follow is mainly based on Kim (1997) and Kim *et al*. (2003).

4.4.1 Spatial lag model

According to Kim *et al*. (2003) spatial-lag model is analogous to an autoregressive time-series model. In the hedonic spatial-lag model, nearby or neighbouring observations of housing prices partially explain local housing price, where the definition of "neighbours" is considerably more complex than in the time-series context. Spatial-lag models implicitly assume that the spatially weighted average of housing prices in a neighbourhood affects the price of each house (indirect effects) in addition to the standard explanatory variables of housing and neighbourhood characteristics (direct effects). It is particularly appropriate in two situations. First, there is structural spatial interaction in the market and the modeller is interested in measuring the strength. Second, the modeller is interested in measuring the true effect of the explanatory variables, after the spatial autocorrelation has been removed, similar to a first-difference approach to time series. Both situations are relevant to this study. The first situation can indicate the strength of spatial autocorrelation in different sub-markets models. This points to the extent of spatial autocorrelation as associated with a segmentation approach. The second situation can reveal the true effects of the structural, accessibility and neighbourhood variables used in the models.

A spatial-lag hedonic housing price model can be written as follows (Bowen et al., 2001):

$$P = \alpha + \rho\, WP + X_1\beta_1 + X_2\beta_2 + X_3\beta_3 + \varepsilon$$

Where P is the vector of housing prices; α is a constant term; ρ[8] is a spatial autocorrelation parameter; W is a *n x n* spatial weight matrix (where n is the number of observation); X_1 is a matrix with observations on structural characteristics; X_2 is a matrix with observations on accessibility characteristics; X_3 is a matrix with observations on neighbourhood quality variables; and ε assumed to be the random errors. The null hypothesis is $\rho = 0$. If ρ significantly departs from zero, the null hypothesis is rejected and spatial lag dependence is said

[5] The general form of the correlation matrix is shown as $K = [(I - \lambda W)'(I - \lambda W)]^{-1}$ (Dubin, 2003) where I denotes the n x n identity matrix.

[6] 1) Inverse distance squared; 2) 600 metres limit; 3) The closest neighbour; 4) Four closest neighbours; and 5) latitude-longitude.

[7] By employing 293 observations of dwelling sales price for Spain.

[8] In this case, the parameter ρ can be interpreted to indicate the extent to which variation in housing unit prices can be accounted for by the average of housing unit prices within whatever designation of contiguity is used to specify the weight matrix, W (Bowen *et al*., 2001). W in this study is based on 6 planar data on average as per specified by the *fdelw2* function (as per email communication with Pace dated 3rd March 2005) embedded in Spatial Econometric Tools, the programme that runs on the matlab software.

to occur.

As shown by Kim et al. (2003), this equation can be written as $P = (I - \rho W)^{-1} X\beta + (I - \rho W)^{-1} \varepsilon$. The presence of $(I - \rho W)^{-1}$ makes the structure of the error covariance matrix quite complicated regardless of the structure of the original covariance matrix Ω. According to them, unlike the time series case (one direction) each error term is correlated with every other error term in two dimensions. Thus, they argue that the Generalized Least Squares (GLS) or the Estimated Generalized Least Squares (EGLS) estimator, which is an unbiased estimator in serial autocorrelation, no longer holds for the spatial lag model. Further, they explain that owing to the presence of the spatial lag term on the right hand side of the above equation, the error will be correlated with the dependent variable (WP). Therefore, they conclude that OLS estimates will be biased and inconsistent.

4.4.2 Spatial error model

In contrast to spatial lag model[9], the spatial error model does not include indirect effects but is based on the assumption that there is one or more omitted variable/s in the hedonic price equation and that the omitted variables vary spatially. Due to this spatial pattern in the omitted variables, the error term of a hedonic price equation tends to be spatially autocorrelated.

Therefore, the solution to spatial error autocorrelation, in principle, is the specification of the proper parameter that is common to all of the observations. If, however, the true neighbourhoods are not known, neighbourhood indicators typically defined over census tract or block groups, or over school districts or political boundaries are used. However, if the indicators used do not properly describe the neighbourhood, it may not solve the spatial autocorrelation problem.

The spatial error model is appropriate when there is no theoretical or apparent spatial interaction and the modeller is interested only in correcting the potentially biasing influence of spatial autocorrelation, due to the use of spatial data. In other words, the interest focuses on obtaining the most efficient estimates for the coefficients in the hedonic model and in ensuring that inference is correct. According to Willhemsson (2002a), the spatial error model is the most popular model and is widely used in real estate economics. Consistently, as shown by Suriatini (2005), this model appears the best spatial model for most cases in her study. The spatial error model can be written as follows[10] :

$$P = \alpha + X_1\beta_1 + X_2\beta_2 + X_3\beta_3 + u$$
$$u = \lambda W + \varepsilon$$

Where P is the vector of housing prices; α is a constant term; W is a n x n spatial weight matrix (where n is the number of observation); X_1 is a matrix with observations on structural characteristics; X_2 is a matrix with observations on accessibility characteristics; X_3 is a matrix with observations on neighbourhood quality variables; λ is the spatial autoregressive coefficient; u is the spatially correlated error; and ε assumed to be the random errors. The null hypothesis is $\lambda = 0$. If λ significantly departs from zero, the null hypothesis is rejected, and spatial error dependence is said to occur.

5. Conclusion

This paper described the issue of spatial autocorrelation in the context of hedonic modelling of housing markets. It outlined three main causes of spatial autocorrelation namely property characteristics, valuation process and mis-specification of hedonic models. Meanwhile, three ways of examining spatial autocorrelation are whether it is positive or negative, spatial lag or spatial error, and isotropic or anisotropic. In dealing with spatial autocorrelation, spatial statistics can be useful because it can detect and model explicitly spatial autocorrelation. Moran's I and the Lagrange Multiplier are two common detection tests used. Geostatistic and spatial weight matrix are two main approaches for explicit modelling of the error term of the hedonic model. The paper stressed that the spatial weight matrix is regarded as more suitable for real estate studies involving economic analysis. Many real estate studies being referred to in the above discussion have come particularly from the USA and a few other countries, but excluding Malaysia. Thus, it would be interesting to see similar evidence coming from real estate studies that employ cross sectional data of other countries such as Malaysia, where no evidence of spatial autocorrelation consideration in hedonic price modelling has been reported.

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[9] This represents the computationally simplest case of spatial hedonic modelling (LeSage and Pace, 2004).

[10] Adapted from Kim *et al*. (2003) who do not show the constant term explicitly in the formula but has it in discussion.

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