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POSTCODE OR CENSUS GEOGRAPHY? AN EXAMINATION OF NEIGHBOURHOOD CLASSIFICATION FOR HOUSE PRICE PREDICTIONS

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ABSTRACT

While various neighbourhood definitions, classification approaches and scales have been used for analysing housing market, there remains a lack of consensus on which classification is best suited. In this study we empirically evaluate two widely used classifications: the postcode and census geography by using all individual London house sales during the period of 2011-2014 through a multilevel modelling approach. The aim is to identify which classification better represents the underlying processes and provides more accurate price predictions. This study has the implication for housing market analysis at national scales and the methodology could be used more widely.

Keywords: house prices, neighbourhood classification, housing submarket, predictive accuracy

1 INTRODUCTION

While extensive research consistently shows that neighbourhoods have strong effects on house prices (Ridker and Henning, 1967; Stegman, 1969; Evans, 1973; Lerman, 1979; Dubin 1992; Orford 2002), the definitions and scales of neighbourhoods analysed vary markedly[1]. Some use existing spatial units such as postcode areas or aggregate these to form larger neighbourhoods. Others construct bespoke neighbourhoods either spatially or aspatially based on a range of criteria, such as the characteristics of individual dwellings and/or their neighbourhood. Ideally, neighbourhood definition should coincide with the scale of the actual processes of house prices (Fotheringham, Charlton, and Brunsdon 2002) but there is little theoretical insight into this.

In this study, we will work under a multilevel modelling (MLM) framework to empirically compare two alternative neighbourhood classifications: one is based on geographical contiguity (postcode geography) and the other considers both spatial contiguity and social homogeneity through census geography. Both classifications are used in the analysis of all the house sales (404,795 transactions) in London during 2011-2014. MLM is used because it sees houses as nested in neighbourhoods and analyses at individual house level and neighbourhood scales simultaneously (Jones and Bullen, 1993). The latent effects of the unmeasured neighbourhood attributes, representing what might be called reputation or attractiveness, can also be estimated and used to predict house price, potentially increasing the predictive accuracy. Another benefit of using MLM is that multiple scales of neighbourhoods can be analysed simultaneously. This allows the decomposition of house price variations to different neighbourhood scales and thereby the assessment of the importance of neighbourhood and its scale effect on prices. To explore and minimise the risk of Modifiable Area Unit Problem (MAUP) (Openshaw, 1983), we have considered multiple neighbourhood levels for both of the classifications as in Flowerdew et al. (2008). Much past comparison work has used very small samples (e.g. 565 transactions in Watkins, 2001) or imprecise prices and addresses (e.g. Bourassa et al., 1999). In contrast the geo-coded Land Registry data used here are large scale, high quality and has fine geographical resolution.

The structure of this paper is as follows. In section 2, the theoretical background on neighbourhood classification and the empirical comparison of alternative classifications are both presented. This is followed in section 3 by the research design, including data, methodology, details of the two neighbourhood classifications as well as performance evaluation criteria. In section 4, the results of the comparison are presented while some conclusions are drawn in the final section.

[1] Throughout the paper, we do not distinguish neighbourhood and submarket and use them interchangeably, although some literature states that submarket is bigger than neighbourhood (for example, Borst, 2007). To our view, this simply represents different scales of neighbourhoods, which can be modelled at nested levels in the multilevel framework.

2 OVERVIEW OF NEIGHBOURHOOD CLASSIFICATIONS

In this section, we provided a brief overview of the development of neighbourhood classifications both theoretically and empirically.

2.1 Theoretical background

The earliest theoretical work about urban structure is the concentric zone theory (Park et al. 1925). This theory argues that competition for scare urban resources, particularly land, ultimately leads to spatial differentiation of urban space into distinctive ecological 'natural areas', or 'zones', generally taking the form of five concentric rings. Within each zone, people share similar social characteristics because they are under the same ecological constraints, therefore the zone boundaries can be identified by comparing the social characteristics between areas. In the 1960s, new urban housing economic theory emerged and the Access-Space model was developed which views housing unit as a homogenous good with its price declining with distance from the central business district (CBD) (Alonso, 1964; Mills, 1967; Muth, 1969). This is based on the assumption that households under income constraints wish to maximize their utility, or satisfaction, by trading off housing expenditure and costs of accessibility to employment in a monocentric urban setting. However, this theory ignores different quality of housing (Grigsby et al., 1987) including social housing and the purchaser's different preference for properties and locations, such as the good reputation of certain neighbourhoods. There are also no differences in geographical locations except their relative distances to the CBD. These assumptions are far from reality as housing units are heterogeneous goods, consisting of a bundle of structural and neighbourhood characteristics, which combine to determine house prices over and above relative accessibility.

A more empirically driven approach was developed in the 1970s in the form of the Hedonic Pricing Model (HPM) (Rosen, 1974). In effect, this simply regresses house prices on a range of measured attributes of properties and neighbourhoods using Ordinary Least Squares (OLS). The resultant regression coefficients provide the implicit, or hedonic price of each attribute. The hedonic function is conceived as result of spatial equilibrium of supply and demand for the various characteristics, which are assumed to have constant effects on house prices across space. However, Grigsby et al. (1963) argues that there are shifts in the supply and demand due to changes in income, employment and demographic composition of household across space, resulting in distinct but dynamically linked housing submarkets. This view was supported by Straszheim (1975) who segmented the housing market in the San Francisco Bay area into 81 relatively homogenous geographical zones by aggregating the census tracts on the basis of housing stock characteristics, occupants' income and the racial composition of the area. Schnare and Struyk (1976) also argued that mismatched supply and demand results in local equilibriums and they classified the Boston housing market into smaller submarkets based on the average income level and census geography but they did not find empirical support for submarkets.

2.2 Empirical operationalisation of neighbourhood classifications

Almost all authors agree that meaningful neighbourhood delineation helps the understanding of price formation processes and improves the predictive accuracy of house prices. In the 34 empirical studies from 1975 to 2009 surveyed by Jones and Watkins (2009), only three studies (Schnare and Struyk, 1976; Ball and Kirwan, 1977; Kauko, 2004) do not support the need to identify neighbourhoods. But there is a continued lack of agreement on neighbourhood definitions, classifying criteria and approaches, which often results in conflicting findings. The varied number of neighbourhoods (ranging from just 2 to 372 amongst the 34 studies) and different spatial scales also contribute to these somewhat inconsistent results.

Neighbourhood classification can be broadly grouped into three approaches: spatial, aspatial and hybrid (Watkins, 2001). The spatial approach requires neighbourhoods to be comprised of adjacent geographical areas (Palm, 1978). Typical examples of this approach are pre-existing spatial units, such as administrative units, school districts, postcodes and parliamentary constituencies. There is no necessary homogeneity within such pre-existing entities (Bourassa et al., 1999), either socially or in terms of housing stock. This approach is convenient, straightforward and cost effective and has been frequently used in housing market research. However, the pre-existing boundaries are generally created for other purposes such as mail delivery, school enrolment or voting and do not necessarily coincide with the boundaries which drive the processes that generate house prices. In addition, they are also prone to the MAUP which could lead to improper analysis at the wrong spatial level and produce biased estimates (Helbich et al., 2013).

The aspatial approach defines neighbourhoods as homogenous units consisting of properties with similar characteristics or people who share similar attributes, for example, property type (Allen et al., 1995), floor area and lot size (e.g. Bajic, 1985), social economic composition (Feitelson, 1993), income (Schnare and Struyk, 1976), ethnicity (Palm, 1978), and social or political identify (Megbolugbe, Hoek-Smit, and Linneman, 1996). This approach generally combines data reduction techniques such as Principle Component Analysis (PCA) and cluster analysis, for example, K-means clustering, to construct neighbourhoods so that the observations within the same neighbourhood type are more similar to each other and different from other neighbourhood groupings. For example, Bourassa et al. (1999) used PCA to identify the important factors for house prices in Sydney and Melbourne in Australia based on the individual property and neighbourhood characteristics at the local government area (LGA) level and then applied cluster analysis to segment the housing markets on the basis of those factors. Compared with the spatial approach, this approach is very time consuming and can be unreliable or unstable (Borst and McCluskey, 2008), therefore this approach is not considered in our empirical comparisons.

The third, hybrid approach, combines spatial contiguity and homogeneity criteria in classifying neighbourhoods and typical examples of this are the use of census geographies. In the UK, the census geography is constructed post enumeration by aggregating adjacent household into spatially compact areas that are as homogenous as possible in terms of housing type and tenure (Martin 1998). As census boundaries are easily obtainable and many neighbourhood statistics are readily available, census geographies have been frequently used in neighbourhood effects studies (Schnare and Struyk, 1976; Jackson, 1979; Heikkila et al., 1989; Can, 1992). It should be noted though that census geography is created mainly for the census reporting purposes and not specifically for the housing market. Their boundaries do not necessarily describe the real spatial process that generates the house price data. Census data are also generally aggregated at a specific spatial level to ensure confidentiality which may hide the spatial processes of house prices that are actually occurring.

All of the approaches outlined above are rather ‘mechanical’ approaches based on the objective criteria. Neighbourhoods can also be delineated using ‘subjective’ expert opinion such as estate agents and valuers, as in the studies of Palm (1978), Michael and Smith (1990), and Bourassa, Hoesli and Peng (2003). However, this approach demands considerable effort and can be subjective and therefore not suitable for large scale analysis of, for example, a large metropolitan area.

2.3 COMPARISON OF DIFFERENT APPROACHES

Although there are various studies on neighbourhood effects on house prices, there are very few empirical studies that compare the effectiveness of different neighbourhood classifications. Of the previous ten empirical comparisons from 1986 to date, one study supports the aspatial approach (Bourassa et al., 1999), one prefers the expert-defined boundaries (Bourassa, Hoesli and Peng, 2003), three favour the spatial approach (Clapp and Wang, 2006; Helbich et al., 2013; Leishman et al.2013) and three support the hybrid approach (Watkins, 2001; Goodman and Thibodeau, 2007; Bourassa, Cantoni, and Hoesli, 2010). The remaining two studies do not find major differences in the predictive accuracy between the spatial and the hybrid approach (Goodman and Thibodeau, 2003) or between spatial and expert approach (Chen et al., 2007). The majority of these studies either fitted a separate HPM for each submarket or specified fixed-effect models (Bell and Jones, 2015) with a set of dummy variables representing each neighbourhood. But these two approaches are nothing more than fitting a separate regression line for each neighbourhood. There is no overall model fitted to all the data simultaneously and they are consequently unable to reveal the between-neighbourhood variations at multiple scales. Goodman and Thibodeau (2003) and Leishman et al. (2013) used the MLM approach, but neither of them analysed neighbourhood effects at multiple scales. Leishman et al. (2013) observed that models with finer spatial scales tend to predict more accurately, but they did not take into account the model complexity. Both of the studies also have considerably smaller datasets than this study.

It is clear that different neighbourhood definitions, criteria, classification approach and algorithm, scales of analysis, datasets, and performance measures and how neighbourhood are modelled have all contributed to the inconsistent findings. Further empirical comparison for the same dataset under the same modelling framework which can deal with multiple neighbourhood scales is needed; hence this study specifies two five-level models to compare the two widely used neighbourhood classifications at four spatial scales: postcode geography, a spatial approach and census geography, a hybrid approach[2].

3 RESEARCH DESIGN

A complete record of house sales (411,544 samples) in Greater London during the period of 2011-2014 was obtained through a highly credible source, the Land Registry for England and Wales. Each transaction record contains the actual sold price, date of the sale, address, unit postcode, property type (detached houses, semi-detached houses, terraces or flats), duration (leasehold or freehold), and whether the property is newly-built. Each sale is then geocoded based on the unit postcodes of properties, represented by the easting and northing of UK Grid references. After removing the incomplete or incorrect records (6,749 samples or 1.6% of the original samples)[3], a total of 404,795 samples were available for this study.

3.1 Methodology: Multilevel modelling

Multilevel modelling is proposed for this research as it can deal model micro-relations (at house level) and macro-relations (at neighbourhood level) simultaneously. In the housing context, houses can be viewed as nested in neighbourhoods, which potentially can also have multiple. Each scale can be specified as a level and a variance term at each level summarises the between-neighbourhood price variations at that level, revealing the relative importance of different neighbourhood scales. In a basic two-level random intercept model with a single predictor at house level, for example, house type (with 1 being detached house and 0 being non-detached property), the micro-equation can be expressed as:

$$\boldsymbol{y_{ij} = \beta_{0j} + \beta_1 x_{1ij} + \mathrm{e}_{ij}} \tag{1}$$

Where y_{ij} and x_{1ij} represent house price and type for level-1 house i in level-2 neighbourhood j, respectively. The random residuals e_{ij} represent the price deviations of house i within-neighbourhood j, which are assumed to be mutually independent and follow a Normal distribution with zero mean and a constant variance, namely $e_{ij} \sim N(0, \sigma_e^2)$. The term β_{0j} describes the mean price for non-detached houses in neighbourhood j and is allowed to vary around the overall mean across different neighbourhoods. It is described by a macro-equation:

$$\boldsymbol{\beta_{0j} = \beta_0 + u_{0j}} \tag{2}$$

Where β_0 is the mean price across all neighbourhoods for non-detached properties and the terms u_{0j} are the neighbourhood-level random terms at level 2, representing the unexplained price differentials of neighbourhood j from the mean price of all neighbourhoods. The u_{0j} are also assumed to be mutually independent and following a Normal distribution with zero mean and a constant variance $\sigma_{u_0}^2$, that is $u_{0j} \sim$N $(0, \sigma_{\boldsymbol{u_0}}^2)$. Combing the micro-model and macro-model results the following equation:

$$\boldsymbol{y_{ij} = \beta_0 + \beta_1 x_{ij} + (u_{0j} + \mathrm{e}_{ij})} \tag{3}$$

The first part of the combined equation is called the fixed part, representing the means and the second part (within the bracket) is called the random part, representing the unexplained price differentials. House prices now consist of the mean price across the whole study area (β_0) for non-detached property, the marginal price for detached property across the city (β_1), plus a premium or discount (u_{0j}) for neighbourhood j and price deviations at individual house level (e_{ij}). The variance of σ_{uo}^2 and σ_e^2 summarise the unexplained price variations between neighbourhood and within neighbourhood, respectively, after accounting for the individual property types. They can be used to calculate the Variance Partition Coefficient (VPC)=$\frac{\sigma_{uo}^2}{\sigma_e^2 + \sigma_{uo}^2}$, the proportion of the total unexplained variance accounted for by neighbourhoods, given the measured variables, property type in our example.

[2] Space precludes the discussion of an aspatial classification but we found in practice that the typology of the aspatial classification by Longley and Singleton (https://files.datapress.com/london/dataset/london-area-classification/2011%20LOAC%20Report.pdf) performed less well than either classification used here.

[3] For example, some records do not have unit postcodes or the durations of the properties, or the postcodes specified in the records do not exist at the time of the sale.

The standard 2-level MLM can be easily extended to three or more levels to allow neighbourhood effects to be examined at multiple scales, for example, small-scale neighbourhoods nested in bigger regions. Building on the previous two-level model, the micro-and macro-equations in a three-level random-intercept model can be expressed as:

Level 1: $\boldsymbol{y_{ijk} = \beta_{0jk} + \beta_1 x_{1ijk} + \mathrm{e}_{ijk}}$ (4)

Level2: $\boldsymbol{\beta_{0jk} = \beta_{0\mathrm{k}} + u_{0jk}}$ (5)

Level 3: $\boldsymbol{\beta_{0k} = \beta_0 + v_{0k}}$ (6)

Substituting the level-3 macro-equation in the level-2 and then level-1 model, we get the following combined equation:

$$\boldsymbol{y_{ijk} = \beta_0 + \beta_1 x_{ijk} + (v_{0k} + u_{0jk} + \mathrm{e}_{ijk})} \quad \textbf{(7)}$$

Where y_{ijk} and x_{1ijk} represent the house price and house-type for house i in level-2 neighbourhood j, in level-3 region k, respectively. The fixed part represents the means of all non-detached properties and the differential for detached properties across all regions. The random part represents the unexplained regions differentials (v_{0k}) from the overall mean, the neighbourhood differentials (u_{0jk}) from that regional mean to which the neighbourhood belongs, and individual property price deviation (e_{ijk}) from that neighbourhood mean. Similarly, the total unexplained variance can now be decomposed into three levels, with $\frac{\sigma_{vo}^2}{\sigma_e^2 + \sigma_{uo}^2 + \sigma_{vo}^2}$ being the proportions accounted for by regions and $\frac{\sigma_{uo}^2}{\sigma_e^2 + \sigma_{uo}^2 + \sigma_{vo}^2}$ being accounted for by neighbourhoods, after considering the individual property type.

In this example, the term u_{0j} and v_{0j} are latent variables representing the ‘desirability’ of neighbourhoods and regions. These unobserved characteristics of neighbourhoods and regions play a role ‘behind the scenes’ in house prices (Snijders & Bosker, 1999) and these latent, unmeasured but modelled effects can be utilised for house price prediction. The local estimates of neighbourhood residuals are also precision-weighted, “shrunken” towards the overall mean relationship for all neighbourhoods by borrowing strength from other neighbourhood (Jones and Bullen 1994). This is especially useful for neighbourhoods with a small number of observations.

3.2 Postcode and census geography in the UK

The UK postcode geography was originally created for mail sorting and delivery. It has a naturally nested hierarchical structure where the unit postcode is nested in a postal sector, which is in turn nested in a postal district and then a postal area. In this study, we specified a five-level model to explore price variations simultaneously at various spatial scales, with 404,795 house sales coming from 100,067 unit postcodes, which are nested in 1,004 postal sectors and in turn nested in 278 postal districts and 21 postal areas.

The 2011 UK census geography was created for the release of neighbourhood statistics at a national scale. An Automated Zone Procedure (AZP) (Openshaw, 1977) was used to create the smallest census geography, Output Area (OA), by aggregating the adjacent unit postcodes into regular-shaped and spatially compact areas constrained by certain population and household thresholds (Cockings et al., 2011)[4]. OAs are designed to be as socially homogenous as possible in terms of housing type (detached, semi, terraced and flat) and tenure and are then used as building blocks to construct bigger yet still compact lower-layer and middle-layer super output areas (LSOAs and MSOAs), using the same AZP procedure but with different population and household thresholds[5]. For this classification, we also specified a five-level structure where house sales are nested in 24,614 OAs, then in 4835 LSOAs and 983 MSOAs, which are in turn nested in 33 London Boroughs including the City of London.

[4] The 2011 OAs for England and Wales have a lower and upper household threshold of 40 and 250 (the population restricted within the range of 100-625). The output geographies for Scotland and Northern Ireland were created using a similar process but with different thresholds.

[5] The lower and upper household threstholds for LSOAs are 1,000 and 3,000 with the population restricted between 400 and 1,200. The household numbers in MSOA are resticted to be 5,000-15,000 with the population within 2,000-6,000 range.

3.3 Performance evaluation

As some of the previous empirical studies find that different performance measures could result in conflicting results, we have jointly considered three performance measures to reach a balanced overall comparison of competing models: predictive accuracy, goodness-of-fit and model explanatory power. For predictive accuracy, we adopted a refined index of agreement as suggested in Willmott et al. (2012) as this index is related to the mean average error but it is dimensionless and not affected by the scales of the dependent variable. The refined index of agreement, d_r, can be expressed as

$$d_r = \begin{cases} 1 - \frac{\sum_{i=1}^{n}|\hat{y}_i - y_i|}{2\sum_{i=1}^{n}|y_i - \bar{y}|}, & \sum_{i=1}^{n}|\hat{\boldsymbol{y}}_i - \boldsymbol{y}_i| \le 2\sum_{i=1}^{n}|\boldsymbol{y}_i - \bar{y}| \\ \frac{2\sum_{i=1}^{n}|y_i - \bar{y}|}{\sum_{i=1}^{n}|\hat{y}_i - y_i|} - 1, & \sum_{i=1}^{n}|\hat{\boldsymbol{y}}_i - \boldsymbol{y}_i| > 2\sum_{i=1}^{n}|\boldsymbol{y}_i - \bar{y}| \end{cases}$$

where y_i is the observed value of the dependent variable, $\hat{y}$ is the predicted value, $\bar{y}$ is the true mean of the observed value, and n is the number of samples. This index of agreement indicates the sum of the magnitudes of the predictive error relative to the sum of the magnitudes of the perfect-model ($\hat{\boldsymbol{y}}_i = \boldsymbol{y}_i$, for all i) deviation and observed-deviations from the observed mean. The predictive accuracy is evaluated on a hold-out sample, the test set, which has not been used to estimate the parameters in the model calibration (the training set). In order to make the use of the latent neighbourhood effects at the smallest spatial scales for both classifications and to ensure a good mixture of the test set, a stratified sampling strategy based on the unit postcode is used. A random sample from each unit postcode is put in the test set unless there is only one sample in that unit postcode, in which case it is left only in the training set. The test set consists of 75,089 samples, around 19% of the total dataset.

The Deviance Information Criterion (DIC) is used to evaluate the model fit while penalizing the model complexity. As the traditional goodness-of-fit measures, such as Akaike Information Criterion (AIC) and Bayesian Information Criteria (BIC) requires the count of the effective (nominal) number of parameters which is less clear in MLM due to the hierarchical data structure and the latent effects which do not each contribute a whole degree of freedom as they are specified to come from a distribution with a common variance. Therefore, DIC is more suitable for comparing complex multilevel models (Spiegelhalter et al., 2002). DIC can be described as DIC = Dbar + pD, where Dbar is the posterior mean of the deviance – the badness of fit and pD is the 'effective' number of parameters (pD) consumed in the fit.

The final performance measure is the explanatory capacity of the models. Through MLM, the relative importance of neighbourhood scales can be assessed by comparing the unexplained price variations at each level. This provides further insights into the neighbourhood effects on house prices at different spatial scales.

4 MODEL RESULTS AND DISCUSSION

In this section, we present the model results using postcode (model 1) and census geography (model 2). In both models the dependent variable is ten times of the natural logarithm of house prices expressed in thousands of pounds[6]. The predictor variables include house characteristics (the reference property category is a non-new build, freehold, and semi-detached property) and the time of the sale (expressed in numerical form with the beginning of the study period being zero). The property characteristics are specified as full interactions representing 16 combinations of property type. The dates of the sales are modelled as a third order polynomial to capture the time trend in house price changes. Consequently the between-neighbourhood differences are estimated after taking account of the composition of house types within each neighbourhood and controlled for time-based inflation. The models are estimated as Bayesian models through Markov Chain Monte Carlo (MCMC) procedures (Jones and Subramanian, 2014) to obtain the "effective" degrees of freedom (pD) and DIC for each model.

The index of agreement for model 1 (0.84) is higher than model 2 (0.77), implying that the predictive accuracy for the out-of-sample properties using the postcode classification is better than census geography. The model fit – the DIC - applied to the full sample using postcode after considering the effective degree of freedom is also better than through census geography (see Table 1). This is not surprising as postcode geography have

[6] Log values are used to deal with the positive skew of the house price distribution and this transformation is very successful in achieving conditional Normality. .Multiplying the logs by 10 helps the computational accuracy of the MLwiN program.

been traditionally utilised by many stakeholders in the housing market. Real estate appraisers frequently value properties based on comparison sales of nearby properties within the same postcode area or postcode district. Sellers or their agents also make of good reputations of certain postcodes as their marketing strategies. Buyers also often refine their geographical search criteria using postcode.

Table 1 Comparison of Model Goodness-of-Fit

Models	1-Postcode	2-Census
DIC	1,953,157	2,045,682
pD	74,724	19,952
Nominal df	101,389	30,484

In terms of model explanatory power, we investigated the percentage of unexplained variations by each neighbourhood levels defined in two classifications using the full samples, calculated as VPC (Table 2). For postcode geography, postal areas, district, sector and unit postcode account for 25%, 21%, 8% and 26% of the total unexplained price variations by the model, respectively, that is all the levels of postcode geographies altogether account for 90% of unexplained variations after housing characteristics are controlled for, leaving only 10% at the individual house level. In contract, all levels of census geographies account for 81% of the unexplained variations. The substantially higher proportion of the unexplained price variations accounted for by the postcode than census geographies implies that postcode geographies capture more price variations than census geographies. At the same time, VPC is also related to the intra-class correlations (ICC), which indicates the correlations of house price within the same neighbourhood. The total VPC therefore can be interpreted that the correlations between the prices for two houses of the same type and sold at the same time within the same unit postcode are 0.9 correlated to each other while the prices of two houses from the same OAs are 0.81 correlated. This not only confirms the general conception of the importance of postcode in housing price determination, but also evidences that the autocorrelations between house prices are in fact implicitly modelled through MLM framework.

Table 2 Comparison of price variations at multiple neighbourhood scales

	Model 1: Postcode			**Model 2: Census**		
	Number of units	**Variance (S.E.)**	**VPC**	**Number of units**	**Variance (S.E.)**	**VPC**
level5	21	32.20 (11.67)	0.50	33	25.67 (7.01)	0.56
level4	278	14.65 (1.41)	0.23	983	7.47 (0.37)	0.16
level3	1,004	3.70 (0.21)	0.06	4,835	1.58 (0.05)	0.03
level2	100,067	7.21 (0.05)	0.11	24,614	2.74 (0.04)	0.06
level1	404,795	6.07 (0.02)	0.10	404,795	8.73 (0.02)	0.19
Total VPC by geography			**0.90**			0.81

The latent random effects of the neighbourhoods at the largest scales for both classifications are presented in Figure 1 (postcode) and Figure 2 (London Boroughs) in the order from the least to the most desirable places. The horizontal line of 0 is the predicted mean house price of across the broadest scales of the neighbourhoods. The triangles represent the price differentials (in the same scales of dependent variable, that is ten times of the log prices in thousands of pounds) of the places.). A positive value means a premium for a place and a negative value indicates a discount for that place compared with the mean price across the whole London. For example, the most attractive postal area (WC for Western Central) has a value of 10.42, indicating that the mean house price for that area is 2.8 times of the average house price of Greater London (diving 10.42 by 10 and then exponentiated). In contrast, the least desirable place (DA for Dartford) has a price differential of -6.36, equating to 53% of the average London price. The error bars represents the 95% credible intervals of the neighbourhood price differentials. As seen clearly from Figure 1, there are five postcode areas (Western Central, West, East Central, South West and North West London) commanding significantly higher price than the London average house price while the bottom five areas (Dartford, Romford, Southall, Croydon and Ilford) are significantly unattractive. The desirability of London Boroughs are also presented in a similar fashion, with Kensington and Chelsea, Westminster and Camden at the higher end of the market, commanding 3.5, 2.9 and 2.2 times of the London Average, respectively. These neighbourhood price differentials are estimated without including any neighbourhood-level attributes, and yet some places, particularly at the macro spatial scales, are clearly more desired than others. The macro geography is particularly important and it matters the most in which part of the city the properties are located.

Figure 1 Rank of desirability of Postcode Areas

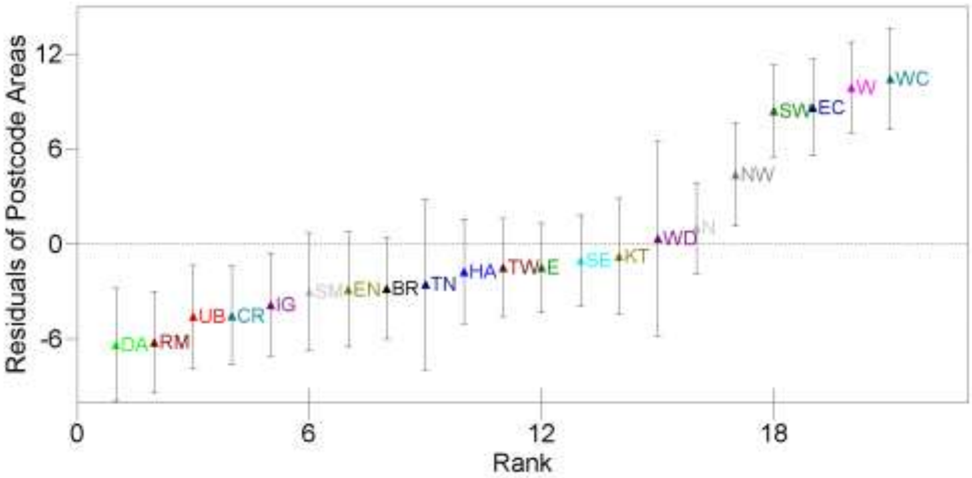
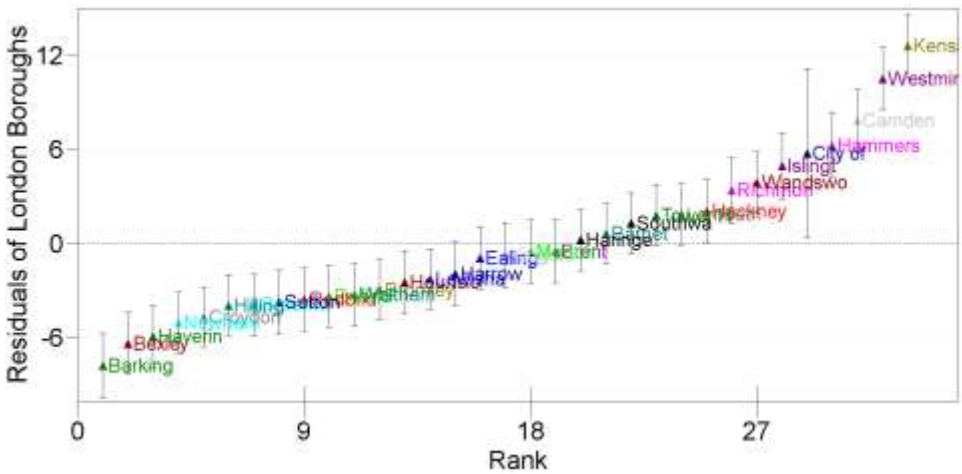
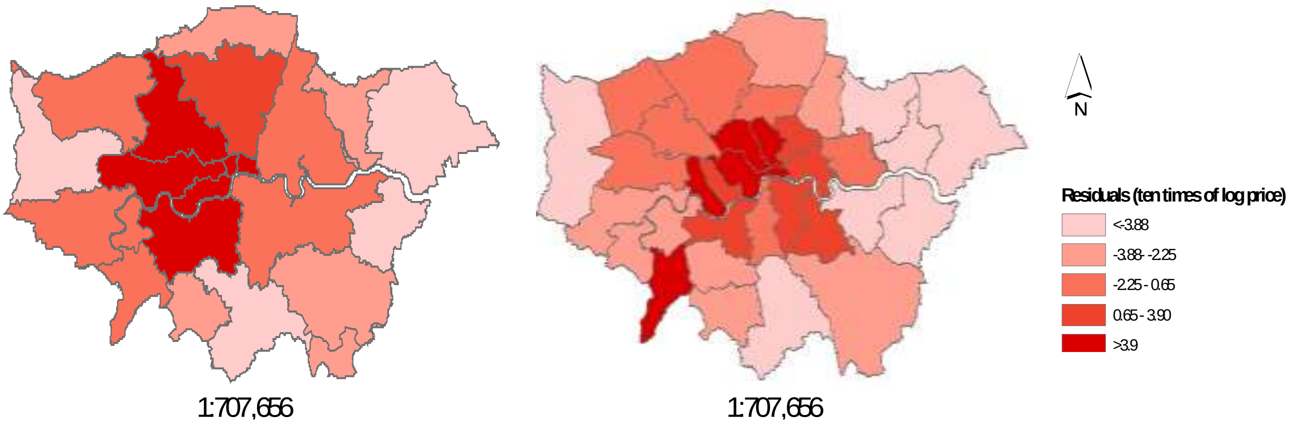


Figure 2 Rank of desirability of London Boroughs



In order to illustrate where the dearer and cheaper places are located, we have also presented the geographical distributions of the price differentials for both postcode areas and London Boroughs (Figure 3). The patterns for both classifications are broadly similar, with the more desirable areas mainly in the west of London while the not-so-popular areas located on the outer fringe of Greater London and to the east of the central core. As the boundaries of London Boroughs do not coincide with the postcode areas, the desirable areas seem to be comparatively smaller.

Figure 3 Geographical distributions of the residuals of Postcode Areas and London Boroughs



(a) Residuals of Postcode Areas   (b) Residuals of London Boroughs

5 CONCLUSIONS

In this study, we compared a spatial neighbourhood classification that requires geographical contiguity (postcode) and a hybrid approach that additionally considers the homogeneity of the places in defining neighbourhood (census geography). Both classifications are investigated at multiple spatial scales. It was found postcode geography performs better in terms of both predictive accuracy and model fit, and accounts for more proportion of the unexplained house price variation than census geography. This contradicts the findings in Fletcher, Gallimore, and Mangan (2000) who did not find much benefit in using postcode areas to classify the UK housing market. One possible reason for this is that their level of analysis is too aggregated. This research casts further doubts on whether spatial contiguity should be jointly considered with homogeneity in neighbourhood classification, as previously argued by many researchers (Watkins, 2001; Goodman and Thibodeau, 2007).

We also demonstrated that neighbourhood should be examined at multiple scales and MLM is a more suitable modelling framework in the neighbourhood effects analysis. In addition to using the existing boundaries as in this study, other bespoke neighbourhood classifications can be added to the future comparison studies utilising the same methodology, for example the UK OA classification, an aspatial approach that delineates neighbourhoods based on the inhabitants' attributes. This study also has the implication for housing market analysis at a national scale and the methodology can be adopted more widely.

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