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Equity in job accessibility and environmental quality in a segmented housing market: The case of Greater London

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Abstract:
Job accessibility and environmental quality are rarely equally distributed in spatial and/or social dimensions within metropolitan regions. Availability of these affects the quality of residential locations, and can be expected to be capitalised into house prices. For prospective house owners, their options will be limited to sub housing markets within certain price bands depending on their available housing budgets. Availability and marginal prices of job accessibility and environmental quality, as well as trade-offs between them, might be different between these submarkets. Using Greater London as the case metropolitan region, this study explored such differences, to shed light on the role of housing market in equity and/or inequity in job accessibility, environmental quality and their interactions. Results of this study show that lower-price submarkets have advantages in job accessibility in terms of marginal price, but are disadvantaged in terms of availability. Differences are more mixed in marginal price and availability between the submarkets for environmental quality. When balancing job accessibility and environmental quality within constrained housing budgets, households in lower-price submarkets would find it relatively easier to gain job accessibility with less sacrifice on environmental quality as compared to those searching in higher-price submarkets, but hard to reach the higher levels of job accessibility that are mainly reserved for the higher-price submarkets.

Keywords: social equity, job accessibility, environmental quality, submarket, hedonic price model

1. Introduction

Job accessibility and environmental quality are important opportunities and resources that contribute to well-being (Grengs, 2010; Rehdanz & Maddison, 2008). Their distributions, however, are often unequal in spatial and/or social dimensions within metropolitan regions, as the distributions can be affected by various factors such as ecological and physical constraints, predefined standards in the planning systems, political activism, and market process (Lucy, 1981; Mitchell, 2005; Talen, 1998).

Regardless of varied concepts of fairness, numerous studies have demonstrated the unequal distributions. For job accessibility, most studies have compared areas resided by different socioeconomic groups and found lower job accessibility is generally associated with poorer socioeconomic conditions (Hernandez, 2018; Lucas, 2012; Slovic et al, 2019). Travel mode and cost have also been considered, as socioeconomically disadvantaged groups normally have less access to cars (Grengs, 2010; Kawabata & Shen, 2007) and high cost of public transport can also be a large barrier for these groups in addition to travel time and distance (Carruthers et al., 2005; El-Geneidy et al., 2016). Some studies focus specifically on accessibility to low-income jobs which is more valuable for socioeconomically disadvantaged groups, and further evidence the disparities against these groups (Elldér et al 2012; Legrain et al., 2016).

For environmental quality, results have been more mixed. While most Northern American studies show that socioeconomically disadvantaged areas tend to experience higher air pollutions, European studies reveal more ambiguous patterns with inconsistent findings (Deguen & Zmirou-Navier, 2010; Hajat, Hsia & O'Neill, 2015; Temam et al., 2017). Much less research has been done on noise, but mixed relationships between socioeconomic condition and noise exposure are also revealed (Dreger et al., 2019). In terms of distribution of greenspaces, lower levels of access are often found in association with poor socioeconomic conditions (Ferguson et al., 2018; Vaughan et al., 2013). However, contrasting patterns also exist with more deprived areas enjoying better access (Barbosa et al., 2007; Kessel et al., 2009), and there are arguments that differences in the definition and measurement of greenspace quality and distribution can lead to biased and conflicting conclusions (Mears & Brindley, 2019).

Job accessibility and environmental quality affect the quality of residential locations, and can be expected to be capitalised into house prices. Based on hedonic price modelling (Rosen, 1974), much research has been devoted to studying the values or implicit prices of individual housing attributes, including job accessibility and environmental quality. Improvements in job accessibility, measured simply as mean distance or travel time to employment centres, or using more complex functional formulations to account for non-linear distance deterrence and competition, are found to lead to substantial increase in house price (Osland & Thorsen, 2008; Ottensmann *et al.*, 2008). Improvements in environmental quality, e,g., reductions in particulate concentration (Kim *et al.*, 2010; Smith & Huang, 1995) and exposure to transport noise (Baranzini *et al.*, 2010; Lake *et al.*, 1998), higher access to greenspaces (Liebelt *et al.*, 2018; McLeod, 1984), are also shown to increase house price, although generally in smaller magnitudes as compared to the effect of job accessibility.

Properties with both high job accessibility and high environmental quality will not only be expensive, but may also be scarce in metropolitan regions, since accessibility and pollution are both externalities of urban agglomeration, and often co-occur in metropolitan regions (da Schio et al., 2019; Higgins et al., 2019). Thus, when choosing properties, prospective house owners often need to make a trade-off between job accessibility and environmental quality within the available and affordable housing market. The trade-off preference may depend on the price ratio of accessibility and environmental quality, and other factors like ranges of available/existing accessibility and pollution levels (Higgins et al., 2019). Napton & Day (1992) shows that many people, including those from high income groups, are willing to trade off air quality for improved accessibility, when options are limited. While in Hamersma et al. (2015), the higher association between perceived highway nuisances and moving intentions indicates residents' preference for environmental quality over accessibility.

As with their uneven distributions, marginal prices of job accessibility and environmental quality, as well as trade-offs between them, may also differ within a metropolitan region. It has long been argued that a unitary metropolitan housing market is unlikely to exist, instead, the market is segmented into submarkets, and capitalisations of housing attributes differ between the submarkets (Goodman & Thibodeau, 1998; Watkins, 2001). Numerous studies have shown the existence and significance of housing submarkets, defined in spatial and/or structural dimensions (Maclennan & Tu, 1996; Wu & Sharma, 2012), by household income groups (Munro, 1986; Schnare & Struyk, 1976), or by empirical cluster analysis (Day, 2003, Keskin & Watkins, 2017). In this study, we define and examine submarkets by price band, since for prospective house owners, their options will be limited to properties within certain price bands depending on their available housing budgets (Hausman & Wise, 1980; Stone, 2006), and thus, within certain patterns of availability and marginal prices of, and trade-offs between, job accessibility and environmental quality.

Therefore, this study aims to explore the potential differences in the availability and marginal prices of, and trade-offs between, job accessibility and environmental quality within metropolitan regions. In particular, this study compares the differences for households with different housing budgets. Greater London was used as the case metropolitan region, and a database of structural, neighbourhood, environmental and accessibility attributes of the sample properties was built for spatial analysis and hedonic price modelling. Submarkets by price band were examined to define housing markets that were affordable for the different household groups. While this study does not debate on equity judgements, i.e., who should get what, findings of this study will shed light on the role of housing market in equity and/or inequity in job accessibility, environmental quality and their interactions in metropolitan regions.

The remaining part of the paper is structured as follows: Section 2 describes the dataset and variables used in this study; Section 3 details the steps of defining submarkets by price bands and developing hedonic price models; Section 4 analyses the results and compares the submarkets; and Section 5 concludes the paper.

2. Dataset and variables

2.1. Case city and sample properties

Greater London was used as the case metropolitan region for this study, and house price data was collected from the Price Paid Data (HM Land Registry, 2017), which contains sales prices of properties in England and Wales submitted to Her Majesty's Land Registry for registration. In total, 85732 sale prices were registered in Greater London during the year 2011 and these were used for this study. The year 2011 was chosen since most of the available data for socio-economic information of London were based on the UK 2011 Census (see Section 2.3).

2.2. Structural attributes

Property type, tenure type and whether new-build, which were provided in the Price Paid Data, were used as structural attributes (Appendix 1). Due to the unavailability of Ordnance Survey's AddressBase data (Ordnance Survey, 2017a) through Edina Digimap for academic research during the time of this study, it was not possible to link each property sale price to building features on map to estimate the floor area and height of the property or the size of the plot, nor was information on number of bedrooms, bathrooms or carparks available from Price Paid Data. Adding these attributes would be expected to further enhance the hedonic models.

2.3. Neighbourhood attributes

Neighbourhood attributes were constructed based on the UK 2011 Census data (Office for National Statistics, 2017a). A list of the used attributes can be found in Appendix 1. All the attributes were on Lower Layer Super Output Area (LSOA) level except the secondary school Ofsted rating which was on ward level. LSOAs are geographic areas for census outputs in England and Wales, generated with intentions to be as consistent in population size, property type and tenure type as possible (Cockings *et al.*, 2011). The minimum and maximum population thresholds of LSOAs are 1000 and 3000, and a LSOA typically has a population of around 1500 (Cockings *et al.*, 2011). Values of these neighbourhood attributes were attached to the house price data according to the LSOAs and wards that the properties were located in.

As would be expected, many of the neighbourhood attributes were highly correlated with each other. To reduce collinearity between independent variables to be entered into the hedonic price models, principal component analysis was used to identify major dimensions of associations between these neighbourhood attributes, and eight principal components were produced to replace the variables. Table 1 lists the components with interpretation.

Table 1. The principal components of neighbourhood attributes.

Component	Variation explained	Cumulative variation explained	Attributes with high positive loading	Attributes with high negative loading	Interpretation
Component 1	25.2%	25.2%	Number of Cars, % Owned Home, % Couple Household, % Detached House, % Semi-Detached Houses, % Age 45-64,	% Car 0, % Flat, % Single without Children, Population Density, % Age 16-29, % Age 30-44, % Rented Home	Neighbourhoods with higher car and home ownerships, more couple households and in less populated areas
Component 2	18.6%	43.8%	% Activity Limited, % Fair or Bad Health, % Education Level 0, 1 or 2, Unemployment Rate	% Activity not Limited, % Good Health, % Education Level 4, Employment Rate	Neighbourhoods where residents are less healthy, less educated, and less likely to be employed
Component 3	8.5%	52.3%	% Black, % Mixed, % Single with Children, % Age 0-15, Unemployment Rate		Neighbourhoods with more black and mixed-ethnic residents, and more children
Component 4	7.9%	60.2%	% White, % UK-born,	% Asian, % Education Others	Neighbourhoods with more white and UK born residents
Component 5	5.6%	65.9%	Ofsted Primary, Ofsted Secondary	KS2 Score, GCSE Score	Neighbourhoods with schools of lower performances
Component 6	5.0%	70.9%	% Education Level 3, % Student	Employment Rate	Neighbourhoods with more university students
Component 7	4.0%	74.9%	% Terraced House, % Car 1		Neighbourhoods with more typical middle-class households
Component 8	3.2%	78.1%	% Empty Space, Crime Rate		Neighbourhoods that are less safe

2.4. Accessibility attributes

A list of the job accessibility attributes used in this study can be found in Appendix 1. All attributes were on LSOA level. Apart from travel time, destination and origin indicators to employment centres by public transport/walk, by cycle and by car obtained from Department for Transport (2017a), we also calculated accessibility to jobs of the seven National Statistics Socio-economic Classification (NS-SeC) classes (Office for National Statistics, 2017b) by car and by public transport respectively, based on Hansen's original formula (Hansen, 1959) taking travel time and number of jobs into account, as well as based on equation (2) in Shen (1998) that in addition takes competition for jobs into account. The NS-SeC is the official socio-economic classification in the UK and classifies the population into eight occupational classes: higher managerial and professional; lower managerial and professional; intermediate occupations; small employers and own account workers; lower supervisory and technical; semi-routine occupations; routine occupations; never worked or long-term unemployed (not used in this study) (Office for National Statistics, 2017b). We differentiated jobs by occupations as their spatial distribution might be different, and accessibility to jobs of certain occupations can be more important than others for the households in each submarket (Legrain et al., 2016). In addition, we added a set of variables of NS-SEC-*i* Jobs by PT/Car, expressed as the ratio of NS-SEC-*i* Jobs by PT and NS-SEC-*i* Jobs by Car, to indicate influence of the relative accessibility by public transport as compared to car.

We also included attributes that describe access to public transport. Public Transport Accessibility Level (PTAL) in Greater London, which is a measure of the accessibility of a point to the public transport network, taking into account walk access time and service reliability, number and frequency, was obtained from Transport for London (2017). Road distance and Euclidean distance to nearest underground station from each property were calculated in GIS using Ordnance Survey's Points of Interest data (Ordnance Survey, 2017b) and MasterMap Integrated Transport Network Layer (Ordnance Survey, 2017c). Since we did not have exact property location data, centroids of postcode units where the properties were located were used as their location points.

2.5. Environmental attributes

Environmental attributes used in this study include air quality, noise, accessibility to greenspaces, and land cover. A list of the attributes can be found in Appendix 1. Air quality data was obtained from London Atmospheric Emissions Inventory 2013 (Greater London Authority, 2017). The metrics include modelled annual average concentrations of NO_2, NO_x, $PM_{2.5}$ and PM_{10}, and Number of days with a daily mean PM_{10} concentrations greater than 50 μg/m^3, at 20 m grid level, covering transport, industrial and commercial, domestic, and miscellaneous emission sources. Noise data was obtained from Strategic Noise Mapping 2012 (Department for Environment, Food and Rural Affairs, 2017) for road and rail noise exposures, using the metric of weighted 24 hour annual average noise level (L_{den}), at 10 m grid level; and from Department for Transport (2017b) for airport noise, which are noise contours around Heathrow Airport showing average 2011 summer day equivalent continuous noise level (L_{Aeq}). Values of air quality and noise attributes were assigned to each property by overlaying air quality and noise maps onto location points of properties in GIS.

Data on access to greenspaces was obtained from Greenspace Information for Greater London (2017a). The metrics include percentages of households at ward level with access to regional parks (within 5 km road network distance), metropolitan parks (2.4 km), district parks (1.2 km), and local, small and pocket parks (400 m), and percentage of households more than 1 km away from an accessible Site of Interest for Nature Conservation. These metrics give a good coverage of different types of greenspaces that are of high amenity and ecosystem service values, and have high potential to influence house price (Panduro & Veie, 2013).

We also calculated land cover ratios of greenspace, water, road, rail, building, and structure within each LSOA, as they are general indicators of built environment characteristics. Land cover data was obtained from Ordnance Survey MasterMap Topography Layer (Ordnance Survey, 2017c) and Greenspace Information for Greater London's open space data (Greenspace Information for Greater London, 2017b) for the calculation.

3. Hedonic house price modelling with submarkets by price band

3.1. Defining potential submarkets by price band

To define the submarkets in an *a priori* manner by price bands, the number of submarkets needed to be determined first. According to the 2011 Great British Class Survey (Savage *et al*., 2013), households in the UK can be divided into seven social classes, among which four housing groups can be identified, as shown in Table 2. Without more relevant stratification schemes available, assuming four submarkets were thought to be appropriate for the purpose of this study. Nevertheless, it should be noted that the housing market in London is distinct from the rest of the UK, and the average house prices could be expected to be much higher than those reported in Savage *et al.* (2013).

Table 2: The four housing groups based on results of the Great British Class Survey (Savage *et al.*, 2013).

Housing group	Average house price	Social class
1	£325k	Elite
2	£177k, £163k	Established middle class, Technical middle class
3	£129k, £127k	New affluent workers, Traditional working class
4	£27k, £18k (both likely to rent)	Emergent service workers, Precariat

To determine the range of each price band that demarcates the submarkets, optimal locations of the three price breakpoints were estimated, by minimising the sums of squared errors of the four resulting hedonic price models (one for each resulted submarket) over all possible alternatives, to achieve the best fit to the data. The calculation was run in R and the package 'strucchange' was used (Zeileis *et al*., 2002). To reduce calculation load, smaller datasets, each containing 10000 house sales randomly selected from the full sample with a limited number of key attributes, were used for the calculation. Five random samples each with two different sets of key attributes were tested and their results compared. The ten sets of estimated breakpoints have similar locations. Based on these locations, we defined the four submarkets to be tested: Submarket 1: ≤ £190,000, 14610 properties; Submarket 2:

£190,000 - £320,000, 33770 properties; Submarket 3: £320,000 - £595,000, 24471 properties; Submarket 4: > £595,000, 12881 properties (Figure 1).

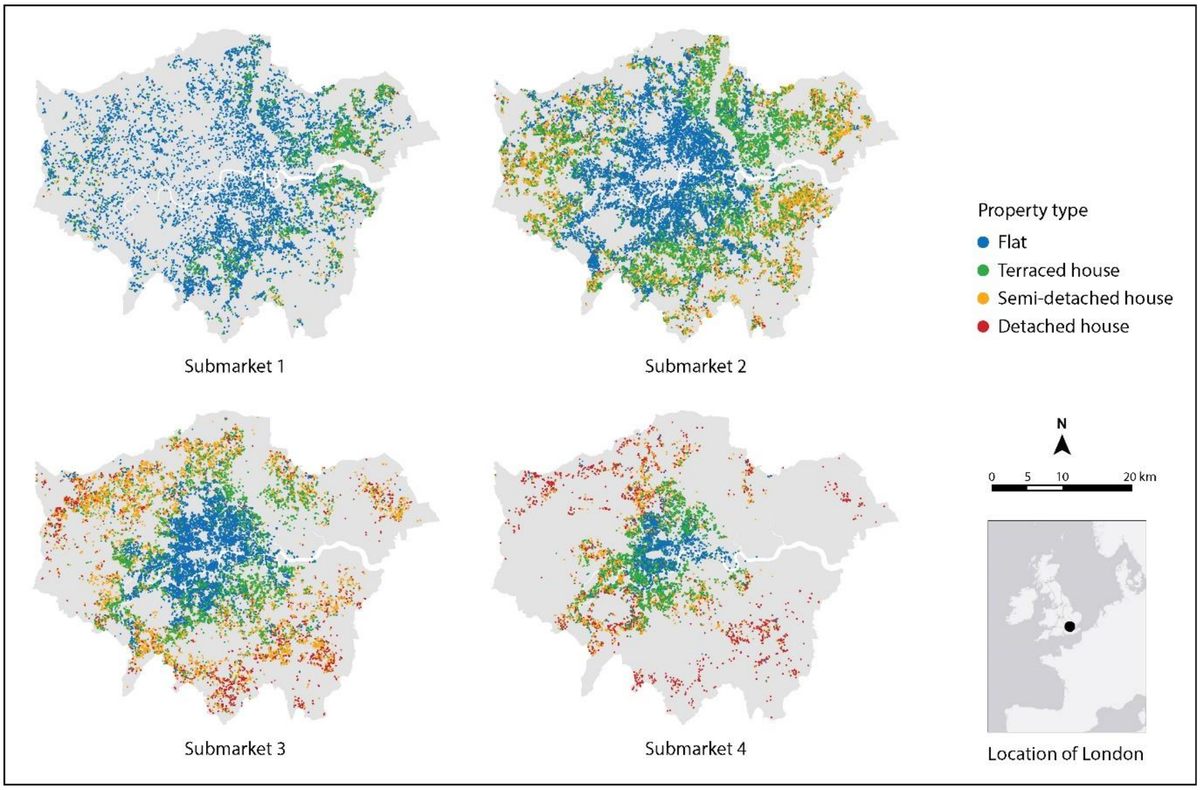

Figure 1. The four submarkets by price band: Submarket 1: ≤ £190,000, 14610 properties; Submarket 2: £190,000 - £320,000, 33770 properties; Submarket 3: £320,000 - £595,000, 24471 properties; Submarket 4: > £595,000, 12881 properties.

3.2. Defining model specification

We used the natural logarithm of house price as the dependent variable and kept the independent variables untransformed. For one reason, this is a usual assumption of functional form in the absence of indications from the literature (Day, 2003); secondly, we were interested in comparing marginal prices of housing attributes relative to the house prices (e.g., per unit increase in air quality costs a certain percentages of the house price) between submarkets. Using untransformed house price as dependent variable would give absolute marginal prices of housing attributes which would also be useful for submarket comparison, however, initial analysis showed that R^2s were generally lower and error terms deviated more from the normal distribution when compared to models using the logarithm of house price as dependent variable. Thus, we decided to use the semi-log functional form.

With the existence of submarkets, it would be expected that model specification that best describes the character of each submarket would differ from each other. However, to be able to compare the marginal prices of housing attributes between submarkets, consistency in model specifications across the submarkets was needed. For this purpose, we first ran an ordinary least square (OLS) regression with backward stepwise variable selection for each submarket, to get model specifications that fit the individual datasets. Then we adjusted variable selections in each model, controlling multicollinearity and significance, as well as taking research interests into account, to achieve the same model specification for the four submarkets. The obtained model specification and the estimated parameters for full sample and the four submarkets are shown in Appendix 2. It should be noted that R^2s of the submarket models are very low. This is probably due to the relatively narrow range of price in each submarket, which means even small variations in price due to error could lead to a low R^2.

3.3. Examining existence of the submarkets

The examination followed the procedure introduced by Schnare & Struyk (1976) which has been commonly used in subsequent studies for testing submarket existence. It uses Chow test to test for significant differences in parameters between the submarket models, which indicate differences in capitalisation of housing attributes between the submarkets, and thus the existence of the submarkets.

Table 4 shows the Chow test results. All the *F* values are larger than the critical values, suggesting that significant differences in model parameters exist between all four submarkets. The Chow test results were further confirmed by comparing the sum of the weighted standard errors of the submarket models to the standard error of the full-sample model. The result shows a large reduction in standard error from 0.377 of the full-sample model to 0.191 with the four submarkets. Thus, there is convincing evidence of the existence of submarkets defined by the four price bands, and that marginal prices of housing attributes are not constant between the four submarkets.

Table 3. Chow test *F*-statistics for the four submarkets

	Sub market 1	Sub market 2	Sub market 3
Sub market 2	2500.014*		
Sub market 3	3871.725*	4187.197*	
Sub market 4	1471.132*	3422.418*	1650.622*

* Significant at 0.01 level

3.4. Spatial regression

Since spatial autocorrelation would normally be expected in house prices (Dubin, 1992; Pace & Gilley, 1997), diagnostic tests for spatial autocorrelation were conducted for each of the four submarket OLS regression models, as well as for the full-sample model. The diagnostic tests were conducted in GeoDa (Anselin *et al.*, 2006), and a distance-based spatial weight with a threshold distance of 200 m was used.

The results show that for all the models, both the Lagrange multiplier tests for spatial error dependence and for spatial lag dependence were highly significant, suggesting existence of spatial autocorrelation. Since in our study, spatial autocorrelation was considered a nuisance, spatial error models were used as the alternative to OLS models to address the issue. Table 4 shows the spatial error models for the four submarkets and the full sample. As expected, the parameters do not differ remarkably from those of the counterpart OLS models. However, the increased values of R^2 and log likelihood and the decreased values of Akaike information criterion and Schwarz criterion of the spatial error models indicate improvements in general model fit. Moran's I test of the model residuals show that spatial autocorrelation were eliminated for Submarkets 1, 3 and 4, but not completely for Submarket 2 and the full sample. This is due to the difficulties in finding a weight distance band that is optimal for all the submarkets and the full sample. Thus, extra caution is needed when interpreting model results of Submarket 2 and the full sample.

Table 4. Hedonic price models for the full sample and the four submarkets, accounting for spatial autocorrelation using spatial error regression.

Variable	Full sample		Submarket 1		Submarket 2		Submarket 3		Submarket 4	
	Coefficient	z	Coefficient	z	Coefficient	z	Coefficient	z	Coefficient	z
Constant	12.3882	300.03	12.0126	261.81	12.4356	610.26	12.8509	368.38	12.989	88.33
Detached House	0.9758	152.65	0.0854	2.3	0.1855	32.91	0.2289	42.62	0.7554	45.91
Semi-detached House	0.698	168.04	0.1595	18.95	0.1487	54.93	0.1528	36.6	0.6091	43.1
Terraced House	0.5784	175.17	0.1549	30.09	0.1053	46.06	0.1283	37.66	0.4963	45.02
New-build	0.1564	19.35	0.0674	6.34	0.0563	13.7	0.0358	6.06	0.1417	5.34
Neighbourhood Component 1	-0.033	-8.6	0.0074*	1.8	-0.0066	-4.21	-0.0229	-9.91	-0.0738	-7.18
Neighbourhood Component 2	-0.1316	-59.1	-0.0188	-7.59	-0.0318	-32.69	-0.0382	-27.56	-0.0774	-13.37
Neighbourhood Component 3	-0.0779	-36.02	-0.0199	-10.76	-0.0242	-27.44	-0.014	-8.93	-0.036	-5.02
Neighbourhood Component 4	0.0456	16.93	0.0081	3.89	0.0066	7.83	0.0157	10.43	-0.0039*	-0.45
Neighbourhood Component 5	-0.2015	-76.1	-0.0198	-6.68	-0.0407	-35.46	-0.0502	-31.76	-0.1561	-24.92
Neighbourhood Component 6	-0.0343	-17.03	-0.0096	-3.88	-0.0098	-10.73	-0.0095	-7.9	-0.0196	-4.8
Neighbourhood Component 7	-0.0639	-26.55	-0.0093	-3.3	-0.017	-15.84	-0.0202	-13.65	-0.0739	-12.33
Neighbourhood Component 8	0.0515	21.26	-0.0163	-5.31	-0.0065	-5.41	0.0065	4.7	0.0861	17.9
NS-SEC-2 Jobs by Car	0.0226	64.53	0.0021	5.74	0.0036	24.45	0.0041	20.11	0.0174	21.06
NS-SEC-2 Jobs by PT/Car	-0.0428*	-0.76	0.0025*	0.05	-0.0266*	-1.21	-0.0696	-2.3	-0.6164	-5.02
% Nature Access Deficiency	-0.0009	-10.04	-0.0002	-2.45	-0.0001	-2.66	-0.0002	-3.84	-0.0007	-3.2
NOx	-0.0019	-12.43	-0.0009	-4.05	-0.0003	-3.5	-0.0002	-2.17	-0.0025	-6.47
Road Noise	-0.0031	-8.7	-0.0004*	-0.82	-0.0008	-4.07	-0.0008	-2.57	0.0027	2.53

Rail Noise	-0.0062	-8.88	-0.0016	-2.03	-0.0015	-4.36	-0.0013	-2.19	-0.0056	-2.1
LAMBDA	0.607	153.13	0.2493	26.91	0.2884	41.54	0.3016	37.1	0.4732	48.25
Observations	85732		14610		33770		24471		12881	
R2	0.711		0.154		0.239		0.215		0.425	
Log likelihood	-31280.63901		2384.976652		22936.78471		11071.45694		-5765.902285	
Akaike info criterion	62599.3		-4731.95		-45835.6		-22104.9		11569.8	
Schwarz criterion	62777.1		-4587.75		-45675.5		-21950.9		11711.6	
Residual Moran's I index (z-score)	-0.0084 (-5.1881)		-0.009 (-1.2296)		0.0182 (4.9887)		0.0037 (0.8949)		-0.0034 (-0.5884)	

*not significant at 0.05 level

4. Results

4.1. Availability of job accessibility and environmental quality

Table 5 shows the means and standard deviations of the variables for the full sample and the four submarkets. Proportion of detached houses increases from Submarket 1 to Submarket 4 and proportion of flat decreases from Submarket 1 to Submarket 4. There is not much difference in *New-build* between the submarkets. Scores of *Neighbourhood Components 2*, *3* and *5*, which indicate typically less favourable neighbourhood characteristics, decreases from Submarket 1 to Submarket 4. Other components indicate neutral characteristics or favourable/unfavourable characteristics but also correlation with remoteness/proximity to central London, and thus the scores show a less clear or less strong pattern across the four submarkets.

Table 5. Descriptive statistics of model variables for the full sample and the four submarkets.

	Full sample		**Submarket 1**		**Submarket 2**		**Submarket 3**		**Submarket 4**	
Observations	**85732**		**14610**		**33770**		**24471**		**12881**	
	Mean	**S.D.**	**Mean**	**S.D.**	**Mean**	**S.D.**	**Mean**	**S.D.**	**Mean**	**S.D.**
Property price (1000 £)	420	494	153	29	251	35	424	75	1161	952
Detached House	0.05	0.22	0	0.05	0.02	0.13	0.08	0.27	0.15	0.36
Semi-detached House	0.17	0.37	0.05	0.22	0.18	0.39	0.22	0.41	0.16	0.37
Terraced House	0.3	0.46	0.21	0.41	0.34	0.47	0.26	0.44	0.36	0.48
New-build	0.04	0.19	0.04	0.19	0.04	0.19	0.04	0.2	0.02	0.15
Neighbourhood Component 1	0	1	0.06	0.75	0.09	0.96	-0.06	1.14	-0.17	1.04
Neighbourhood Component 2	0	1	0.41	0.96	0.15	0.96	-0.2	0.98	-0.47	0.91
Neighbourhood Component 3	0	1	0.44	1.24	0.01	1.01	-0.2	0.83	-0.13	0.76
Neighbourhood Component 4	0	1	-0.04	1.1	-0.09	1.12	0.08	0.89	0.12	0.67
Neighbourhood Component 5	0	1	0.47	0.78	0.28	0.84	-0.18	0.93	-0.93	1.04
Neighbourhood Component 6	0	1	0.04	0.85	0.04	0.95	-0.03	1.06	-0.07	1.16
Neighbourhood Component 7	0	1	0.23	0.86	0.12	0.93	-0.2	1.05	-0.18	1.12
Neighbourhood Component 8	0	1	0.12	0.71	-0.1	0.72	-0.15	1.03	0.34	1.51
NS-SEC-2 Jobs by Car	25.67	13.66	19.27	9.55	22.52	11.69	28.61	14.23	35.61	14.41

NS-SEC-2 Jobs by PT/Car	0.188	0.050	0.181	0.044	0.183	0.046	0.193	0.053	0.196	.056
% Nature Access Deficiency	24.8	29.6	27.1	30.7	26.2	29.8	23.7	28.9	21	28.7
NOx	57.7	16.1	53.4	13.3	55.3	14.4	59.7	17.3	65.1	17.8
Road Noise	51.7	4.4	52.1	4.8	51.9	4.6	51.5	4.2	51.3	3.9
Rail Noise	50.3	2	50.5	2.4	50.4	2.1	50.3	1.7	50.2	1.4

For job accessibility, *NS-SEC-2 Jobs by Car* can be seen as a general indicator of job accessibility in this study, since it was by far the most powerful job accessibility variable when we were testing different model specifications, and it is correlated with other job accessibility variables. It increases from Submarket 1 to Submarket 4, and progressively so for higher price bands. There are also small increases in *NS-SEC-2 Jobs by PT/Car* from Submarket 1 to Submarket 4, which indicates that job accessibility by public transport is more closely associated with higher price bands than job accessibility by car.

For environmental quality, *% Nature Access Deficiency* decreases from Submarket 1 to Submarket 4, while NO_x increases from Submarket 1 to Submarket 4, which can be linked to the higher NO_x concentrations in central London, and the more centralised spatial distributions of properties in the higher price bands. *Road Noise* and *Rail Noise* are largely consistent across the four submarkets, as in each submarket only a small part of the properties with close proximity to major roads or railways are affected by these noises.

In each submarket, properties have different spatial distribution patterns by property type, and property type is also the most dominant attribute in the hedonic models (see Section 4.2). Therefore, we produced density plots and compared distributions and availability of job accessibility and environmental quality by submarket and by property type (Figure 2).

Differences in *NS-SEC-2 Jobs by Car* between submarkets decrease from flats to terraced houses, to semi-detached houses, and to detached houses. For flats, most flats in Submarket 1 have lower *NS-SEC-2 Jobs by Car* while most flats in Submarket 4 have higher *NS-SEC-2 Jobs by Car*. For detached houses, most detached houses in all the four submarkets have lower *NS-SEC-2 Jobs by Car*. While there is still good availability of houses with medium or high *NS-SEC-2 Jobs by Car* in Submarket 4, such options are rare in Submarket 1. The small differences in *NS-SEC-2 Jobs by PT/Car* between submarkets do not vary substantially by property type, and for all the four property types in all the four submarkets, most properties have a *NS-SEC-2 Jobs by PT/Car* between 0.1 and 0.2.

Differences in NO_x between submarkets also decrease from flats to terraced houses, to semi-detached houses, and to detached houses. For flats, most properties in Submarket 1 have NO_x between 25 ug/m^3 and 75 ug/m^3, while most properties in Submarket 4 have NO_x between 50 and 100 ug/m3. For detached house, most properties in all the four submarkets have NO_x between 25 ug/m^3 and 75 ug/m^3. For *% Nature Access Deficiency*, the differences between submarkets are smallest for flats, although not very large for terraced, semi-detached or detached houses either. For all the four property types in all the four submarkets, most properties are in wards with *% Nature Access Deficiency* between 0% and 25%. For *Road Noise* and *Rail Noise*, there are no noticeable differences between submarkets by property type, except in *Road Noise* for detached houses where properties in lower-price submarkets are slightly more likely to be exposed to higher noise levels. Overall, for all the four property types in all the four submarkets, most properties have noise levels around 50 dB (which means below the lowest level of 55 dB in the available noise exposure data used in this study).

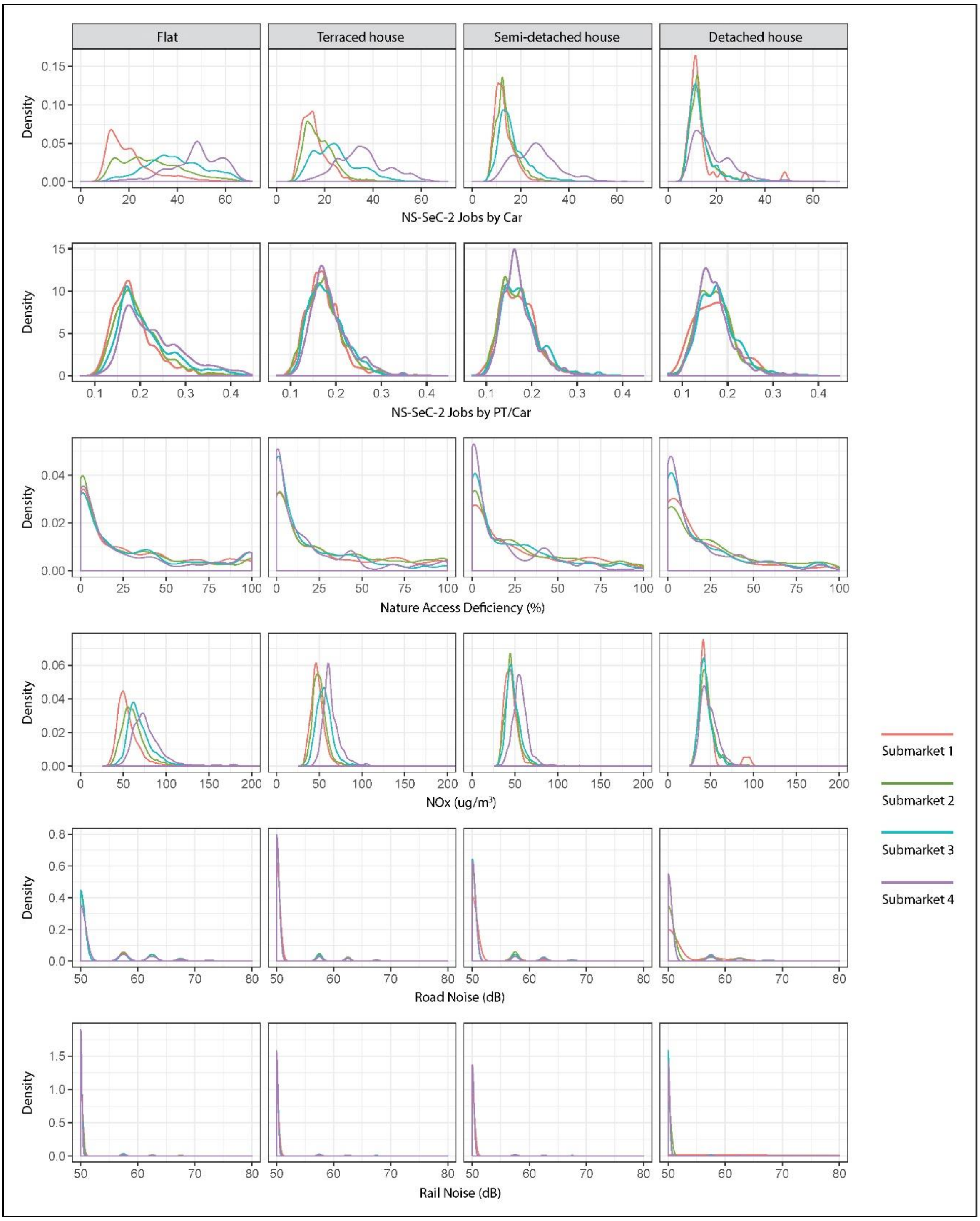

Figure 2. Density plots of job accessibility and environmental quality by submarket and by property type.

In summary, properties in higher-price submarkets are more likely to have higher job accessibility as well as access to nature, but lower air quality. However, these differences are property type dependant, with flats showing the largest differences and detached houses showing the smallest. Households with housing budgets commensurate with the higher price bands can choose over a wide range of options ranging from flats in highly accessible places to detached houses with medium accessibility or in the periphery. Whereas, households with lower budgets are by-and-large priced out of the most accessible places, and if they do not consider flats they can only afford the least accessible locations.

4.2. Marginal prices of job accessibility and environmental quality

The z values in the hedonic price models in Table 4 indicate that property type was the most important attribute affecting house price in all the four submarkets. Marginal prices in Table 6 show that being a house instead of a flat could lead to around 10% to 20% increase in house price in Submarket 1, 2 and 3, and double the price in Submarket 4.

For job accessibility, per unit increase in *NS-SEC-2 Jobs by Car*, which is representative for the overall job accessibility, can increase house price by 0.21%, 0.36%, and 0.41% in Submarket 1, 2, and 3 respectively, and much more rapidly by 1.76% in Submarket 4. Considering the lowest and highest *NS-SEC-2 Jobs by Car* scores in London, potential differences in house prices due to *NS-SEC-2 Jobs by Car* can be as large as 14.56%, 26.24% and 30.39% in Submarket 1, 2 and 3 respectively and 208.38% in Submarket 4. It should be noted though that lowest and highest *NS-SEC-2 Jobs by Car* scores are slightly different in different submarkets, and there might be slight extrapolation issues when applying the London-wide lowest and highest *NS-SEC-2 Jobs by Car* scores to some submarket hedonic price models.

NS-SEC-2 Jobs by PT/Car, which indicates influence of the relative accessibility by public transport as compared to by car, does not have significant impact on house price in Submarket 1 and 2, but decreases house price by 6.72% and 46.01% in Submarket 3 and 4 respectively per unit increase. The negative impacts might be explained by that, as shown during the modelling process, job accessibility by public transport has less impact on house prices than accessibility by car, and increase in *NS-SEC-2 Jobs by PT/Car* is associated with decrease in *NS-SEC-2 Jobs by Car*, which would decrease house prices, and thus *NS-SEC-2 Jobs by PT/Car* overall shows a negative impact on house price. However, variation of *NS-SEC-2 Jobs by PT/Car* in London is small, i.e., difference between job accessibilities by public transport and by car in each LSOA does not vary dramatically between LSOAs. So potential differences in house prices due to *NS-SEC-2 Jobs by PT/Car* will only be as large as 2.59% in Submarket 3 and 20.75% in Submarket 4 where it has a significant impact.

So marginal prices of job accessibility, as relative to the total house price, are higher in submarkets of higher price bands, and particularly, is much higher in Submarket 4. In London, properties in locations of highest job accessibility can potentially be 15% to 30% more expensive than those in locations of lowest job accessibility in Submarket 1, 2 and 3, and triple the prices in Submarket 4.

Table 6. Marginal prices of property type, job accessibility and environmental quality in the four submarkets.

Change in property type, job accessibility and environmental quality	**%Δ House Price**			
	Submarket 1	**Submarket 2**	**Submarket 3**	**Submarket 4**
Terraced House vs Flat	+16.75%	+11.1%	+13.69%	+64.26%
Semi-detached House vs Flat	+17.29%	+16.03%	+16.51%	+83.88%
Detached House vs Flat	+8.92%	+20.38%	+25.72%	+112.85%
NS-SeC-2 Jobs by Car – 1 unit increase	+0.21%	+0.36%	+0.41%	+1.76%
NS-SeC-2 Jobs by Car – highest vs lowest in London	+14.56%	+26.24%	+30.39%	+208.38%
NS-SeC-2 Jobs by PT/Car - 1 unit increase	+0.25%*	-2.62%*	-6.72%	-46.01%
NS-SeC-2 Jobs by PT/Car - highest vs lowest in London	+0.09%*	-1%*	-2.59%	-20.75%
% Nature Access Deficiency - 1% decrease	+0.02%	+0.01%	+0.02%	+0.07%
% Nature Access Deficiency – lowest vs highest in London	+1.98%	+1%	+1.98%	+6.76%
NOx - 1ug/m^3 decrease	+0.09%	+0.03%	+0.02%	+0.25%
NOx – lowest vs highest in London	+21.92%	+7.92%	+5.35%	+49.72%
Road Noise - 1dB decrease	+0.04%*	+0.08%	+0.08%	-0.27%
Road Noise – lowest vs highest in London	+1.19%*	+2.37%	+2.37%	-8.44%
Rail Noise - 1 dB decrease	+0.16%	+0.15%	+0.13%	+0.56%
Rail Noise – lowest vs highest in London	+4.69%	+4.4%	+3.82%	+15.46%

*not significant at 0.05 level in hedonic models

For environmental quality, decrease in *% Nature Access Deficiency* by 1% can increase house price slightly (0.01% - 0.02%) in Submarket 1, 2 and 3, and slightly higher in Submarket 4 (0.07%). So, despite a considerable variation in *% Nature Access Deficiency*, ranging from 0% to 100%, the maximum estimated effect is only 6.76%, in Submarket 4.

Different from access to jobs and nature, results of NO_x indicates decreasing marginal prices of air quality from Submarket 1 to Submarket 3, as 1 ug/m^3 decrease in NO_x can increase house price by 0.09%, 0.03% and 0.02% in Submarket 1, 2 and 3 respectively. However, Submarket 4 still has the highest marginal price, with 0.25% increase in house price for 1 ug/m^3 decrease in NO_x. Considering the lowest and highest NO_x in London, potential differences in house prices due to air quality can be as large as 5.35% in Submarket 3 to 21.92% in Submarket 1, and 49.72% in Submarket 4.

A similar impact was found with *Rail Noise*. The marginal prices of rail noise reduction decrease from Submarket 1 to Submarket 3 although less pronounced, while Submarket 4 still has the highest marginal price. It shows that 1 dB decrease in *Rail Noise* can increase house price by 0.16%, 0.15%, 0.13% and 0.56% in Submarket 1, 2, 3 and 4 respectively. Impact of *Road Noise* shows a different pattern. While it is insignificant in Submarket 1, and increases house price by 0.08% for 1 dB decrease in both Submarket 2 and 3, it decreases house price by 0.27% for 1 dB decrease in Submarket 4. The negative marginal price might be associated with some extremely expensive properties in Submarket 4 in central London where road noise level is high.

Thus, differences in marginal prices of environmental quality between submarkets vary depending on the specific environmental attributes. In general, the marginal prices can possibly be slightly higher in Submarket 1 than in Submarket 2 or 3, but still, like marginal prices of job accessibility, can be by far the highest in Submarket 4.

4.3. Trade-offs between job accessibility and environmental quality

Table 7 shows the trade-offs between job accessibility and environmental quality in each submarket, by units of *NS-SeC-2 Jobs by Car* to give up for a gain in access to nature, air quality and noise reduction, which were calculated by ratios of coefficients from the spatial regression models. The 95% confidence intervals of the ratios, obtained by bootstrapping to account for covariance of the variables, are also provided. Trade-offs of *NS-SeC-2 Jobs by Car* for different property types are also listed for references.

Table 7. Units of *NS-SeC-2 Jobs by Car* to trade-off for environmental quality improvement and property type change, with 95% confidence intervals shown in ().

	Submarket 1	**Submarket 2**	**Submarket 3**	**Submarket 4**
1% decrease in Nature Access Deficiency	0.1 (0.01, 0.15)	0.03 (0.01, 0.04)	0.05 (0.02, 0.06)	0.04 (0.02, 0.05)
1ug/m^3 decrease in NOx	0.43 (0.24, 0.66)	0.08 (0.03, 0.13)	0.05 (-0.004, 0.12)	0.14 (0.16, 0.25)
1 dB decrease in Road Noise	0.19 (-0.42, 0.55)	0.22 (0.11, 0.33)	0.2 (-0.001, 0.3)	-0.16 (-0.35, -0.07)
1 dB decrease in Rail Noise	0.76 (0.17, 1.66)	0.42 (0.18, 0.6)	0.32 (0.17, 0.78)	0.32 (-0.12, 0.45)
From Flat to Terraced House	73.76 (30.51, 89.39)	29.25 (25.77, 30.28)	31.29 (29.02, 35.46)	28.52 (24.23, 28.87)
From Flat to Semi-detached House	75.95 (32.86, 94.54)	41.31 (37.33, 43.71)	37.27 (34.07, 41.54)	35.01 (29.49, 35.29)
From Flat to Detached House	40.67 (-11.21, 75.96)	51.53 (44.66, 53.94)	55.83 (52.02, 63.13)	43.41 (37.78, 44.94)

Generally, households in Submarket 1 need to trade off much more in job accessibility than those in Submarket 2, 3 and 4 to gain improvement in environmental quality, except for road noise reduction where the trade-offs are similar in Submarket 1, 2 and 3 and negative in Submarket 4. For access to nature, 1% decrease in *% Nature Access Deficiency* would require a trade-off of 0.1 unit of *NS-SEC-2 Jobs by Car* in Submarket 1, which is 2 to 3 times the amounts in Submarket 2, 3 and 4. For air quality, 1 ug/m^3 decrease in NO_x would require a trade-off of 0.43 unit of *NS-SEC-2 Jobs by Car* in Submarket 1, which is about 5, 9 and 3 times the amounts in Submarket 2, 3 and 4 respectively. For noise reduction, 1 dB decrease in *Rail Noise* would require a trade-off of 0.76 unit of *NS-SEC-2 Jobs by Car* in Submarket 1, which is about twice the amounts in Submarket 2, 3 and 4.

Nevertheless, considering the low marginal price of job accessibility in Submarket 1, the differences in trade-offs between submarkets may also be interpreted as a relatively easier gain in job accessibility at less sacrifice of environmental quality in Submarket 1.

5. Conclusions

Using Greater London as the case metropolitan region, this study explored differences in availability and marginal prices of, and trade-offs between, job accessibility and environmental quality between sub housing markets of different affordability, defined by price bands (below £190,000, £190,000 - £320,000, £320,000 - £595,000 and above £595,000).

The results show that lower-price submarkets have advantages in job accessibility in terms of marginal price, but are disadvantaged in terms of availability especially when flats are excluded from the property choice. For environmental quality, lower-price submarkets do not necessarily enjoy lower marginal prices, but have higher availability of good air quality than higher-price submarkets although lower availability of access to nature. So, households with limited housing budgets may find it difficult to get higher job accessibility, despite the relatively low price of job accessibility for them. On the other hand, households with high housing budgets can pay more for job accessibility and get more, however, they would thus be more likely to experience the burden of the associated environmental hazards, e.g., air pollution, even if they pay more or are willing to pay more for air quality.

When balancing job accessibility and environmental quality within constrained housing budgets, households in lower-price submarkets would find it relatively easier to gain job accessibility with less sacrifice on environmental quality, as compared to those searching in higher-price submarkets. Nevertheless, this is subject to availability of job accessibility which does not favour lower-price submarkets.

The results thus support and complement findings in existing literature, that socioeconomically disadvantaged groups tend to have lower job accessibility (Lucas, 2012; Slovic et al., 2019), while patterns for environmental quality are less clear or may even be inverse (Barbosa et al., 2007; Dreger et al., 2019; Ferguson et al., 2018; Temam et al., 2017). It indicates that the housing market may have contributed to such patterns by limiting households to sub housing markets that they can afford, which differ in supply and capitalisation of job accessibility and environmental quality.

Authorship contribution

Conceptualization: LJ, AHZ, PK
Data curation: LJ, AHZ, JP
Formal analysis: LJ, AHZ
Funding acquisition,: AHZ, PK
Methodology: LJ, AHZ
Project administration: AHZ
Software: LJ, AHZ
Validation: LJ, AHZ, PK, JP
Visualization: LJ
Writing - original draft: LJ
Writing - review & editing: LJ, AHZ, PK

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Appendix 1. Variables included in analysis in the study.

Variable Name	Description
Structural Attributes	
Terraced House	Whether the property type is terraced house, 0 = No; 1 = Yes
Semi-detached House	Whether the property type is semi-detached house, 0 = No; 1 = Yes
Detached House	Whether the property type is detached house, 0 = No; 1 = Yes
Tenure Type	Whether the property is leasehold or freehold, 0 = Leasehold; 1 = Freehold
New-build	Whether the property is new-build, 0 = No, 1 = Yes
Neighbourhood attributes	
% Age 0-15	% of people aged 0-15 in the LSOA in 2011
% Age 16-29	% of people aged16-29 in the LSOA in 2011
% Age 30-44	% of people aged 30-44 in the LSOA in 2011
% Age 45-64	% of people aged 45-64 in the LSOA in 2011
% Age 65+	% of people aged 65+ in the LSOA in 2011
Population Density	Number of people per hectare in the LSOA in 2011
% Couple with Children	% of couple household with dependent children in the LSOA in 2011
% Couple without Children	% of couple household without dependent children in the LSOA in 2011
% Single with Children	% of lone parent household in the LSOA in 2011
% Single without Children	% of one person household in the LSOA in 2011
% White	% of White people in the LSOA in 2011
% Mixed	% of people of mixed/multiple ethnic groups in the LSOA in 2011
% Asian	% of Asian/Asian British in the LSAO in 2011
% Black	% of Black/African/Caribbean/Black British in the LSOA in 2011
% UK-born	% of UK-born people in the LSOA in 2011
% Economically Active	% of economically active people in the LSOA in 2011
% Economically Active Employee	% of economically active people as employees in the LSOA in 2011
% Economically Active Unemployed	% of economically active people as unemployed in the LSOA in 2011
Employment Rate	Employment rate in the LSOA in 2011
Unemployment Rate	Unemployment rate in the LSOA in 2011
% Education Level 0	% of people with no qualifications in the LSOA in 2011
% Education Level 1	% of people with Level 1 qualifications as the highest level of qualifications in the LSOA in 2011
% Education Level 2	% of people with Level 2 qualifications as the highest level of qualifications in the LSOA in 2011
% Education Apprenticeship	% of people with apprenticeship as the highest level of qualifications in the LSOA in 2011
% Education Level 3	% of people with Level 3 qualifications as the highest level of qualifications in the LSOA in 2011
% Education Level 4	% of people with Level 4 qualifications as the highest level of qualifications in the LSOA in 2011

% Education Others	% of people with other qualifications as the highest level of qualifications in the LSOA in 2011
% Student	% of school children and full-time students age 18 and over in the LSOA in 2011
% Activity Limited a Lot	% of people with day-to-day activities limited a lot in the LSOA in 2011
% Activity Limited a Little	% of people with day-to-day activities limited a little in the LSOA in 2011
% Activity not Limited	% of people with day-to-day activities not limited in the LSOA in 2011
% Good Health	% of people with very good or good health in the LSOA in 2011
% Fair Health	% of people with fair health in the LSOA in 2011
% Bad Health	% of people with bad or very bad health in the LSOA in 2011
KS2 Score	Average point score of pupils eligible for KS2 Assessment in the LSOA in 2010/2011
GCSE Score	Average GCSE and equivalent point score per pupil in the LSOA in 2010/11
Level 3 QCA score	Average Level 3 QCA point score per entry in the LSOA in 2010/11
Ofsted Primary	Catchment-weighted Ofsted primary school rating for the LSOA in 2014
Ofsted Secondary	Catchment-weighted Ofsted secondary school rating for the Ward in 2014
% Car 0	% of household that has no car or van in the LSOA in 2011
% Car 1	% of household that has 1 car or van in the LSOA in 2011
% Car 2	% of household that has 2 or more cars or vans in the LSOA in 2011
Number of Cars	Number of cars per household in the LSOA in 2011
Crime Rate	Rate of crimes per thousand population in the ward in 2010/11 year
% Owned Outright	% of properties owned outright in the LSOA in 2011
% Owned Mortgage	% of properties owned with a mortgage or loan in the LSOA in 2011
% Social Rented	% of properties social rented in the LSOA in 2011
% Private Rented	% of properties private rented in the LSOA in 2011
% Empty Space	% of household spaces with no usual resident in the LSOA in 2011
% Detached House	% of detached houses in the LSOA in 2011
% Semi-detached House	% of semi-detached houses in the LSOA in 2011
% Terraced House	% of terraced houses in the LSOA in 2011
% Flat	% of flats in the LSOA in 2011
Property Sale Rate	Number of property sales per 100 properties in the LSOA in 2011
Accessibility attributes	
PTAL	Average score of Public Transport Accessibility Levels of the LSOA in 2014
% PTAL Poor	% of people in Public Transport Accessibility Level 0-1 (poor access) in the LSOA in 2014
% PTAL Average	% of people in Public Transport Accessibility Level 2-3 (average access) in the LSOA in 2014
% PTAL Good	% of people in Public Transport Accessibility Level 4-6 (good access) in the LSOA in 2014
Travel Time by PT	Travel time to nearest employment centre by public transport/walk from the LSOA in 2011
Travel Time by Cycle	Travel time to nearest employment centre by cycle from the LSOA in 2011
Travel Time by Car	Travel time to nearest employment centre by car from the LSOA in 2011

Small Job Centre by PT	Number of employment centres with at least 100 jobs available by public transport/walk within a reasonable time from the LSOA in 2011
Medium Job Centre by PT	Number of employment centres with at least 500 jobs available by public transport/walk within a reasonable time from the LSOA in 2011
Large Job Centre by PT	Number of employment centres with at least 5000 jobs available by public transport/walk within a reasonable time from the LSOA in 2011
Small Job Centre by Cycle	Number of employment centres with at least 100 jobs available by cycle within a reasonable time from the LSOA in 2011
Medium Job Centre by Cycle	Number of employment centres with at least 500 jobs available by cycle within a reasonable time from the LSOA in 2011
Large Job Centre by Cycle	Number of employment centres with at least 5000 jobs available by cycle within a reasonable time from the LSOA in 2011
Small Job Centre by Car	Number of employment centres with at least 100 jobs available by car within a reasonable time from the LSOA in 2011
Medium Job Centre by Car	Number of employment centres with at least 500 jobs available by car within a reasonable time from the LSOA in 2011
Large Job Centre by Car	Number of employment centres with at least 5000 jobs available by car within a reasonable time from the LSOA in 2011
% Job Centre by PT	% of people with access to employment centres by public transport/walk in the LSOA in 2011
% Job Centre by Cycle	% of people with access to employment centres by cycle in the LSOA in 2011
% Job Centre by Car	% of people with access to employment centres by car in the LSOA in 2011
% Job Centre by Composite	% of people with access to employment centres by composite mode in the LSOA in 2011
NS-SeC-All Jobs by PT	Score of accessibility to all jobs by public transport, taking travel time and number of jobs into account (Hansen, 1959)
NS-SeC-1 Jobs by PT	Score of accessibility to higher professional and higher managerial and administrative jobs by public transport, taking travel time and number of jobs into account (Hansen, 1959)
NS-SeC-2 Jobs by PT	Score of accessibility to higher technical, higher supervisory, lower professional and lower managerial and administrative jobs by public transport, taking travel time and number of jobs into account (Hansen, 1959)
NS-SeC-3 Jobs by PT	Score of accessibility to intermediate jobs by public transport, taking travel time and number of jobs into account (Hansen, 1959)
NS-SeC-4 Jobs by PT	Score of accessibility to jobs as employers in small organisations and as own account workers by public transport, taking travel time and number of jobs into account (Hansen, 1959)
NS-SeC-5 Jobs by PT	Score of accessibility to lower technical and lower supervisory jobs by public transport, taking travel time and number of jobs into account (Hansen, 1959)
NS-SeC-6 Jobs by PT	Score of accessibility to semi-routine jobs by public transport, taking travel time and number of jobs into account (Hansen, 1959)
NS-SeC-7 Jobs by PT	Score of accessibility to routine jobs by public transport, taking travel time and number of jobs into account (Hansen, 1959)
NS-SeC-All Jobs by Car	Score of accessibility to all jobs by car, taking travel time and number of jobs into account (Hansen, 1959)
NS-SeC-1 Jobs by Car	Score of accessibility to higher professional and higher managerial and administrative jobs by car, taking travel time and number of jobs into account (Hansen, 1959)

NS-SeC-2 Jobs by Car	Score of accessibility to higher technical, higher supervisory, lower professional and lower managerial and administrative jobs by car, taking travel time and number of jobs into account (Hansen, 1959)
NS-SeC-3 Jobs by Car	Score of accessibility to intermediate jobs by car, taking travel time and number of jobs into account (Hansen, 1959)
NS-SeC-4 Jobs by Car	Score of accessibility to jobs as employers in small organisations and as own account workers by car, taking travel time and number of jobs into account (Hansen, 1959)
NS-SeC-5 Jobs by Car	Score of accessibility to lower technical and lower supervisory jobs by car, taking travel time and number of jobs into account (Hansen, 1959)
NS-SeC-6 Jobs by Car	Score of accessibility to semi-routine jobs by car, taking travel time and number of jobs into account (Hansen, 1959)
NS-SeC-7 Jobs by Car	Score of accessibility to routine jobs by car, taking travel time and number of jobs into account (Hansen, 1959)
NS-SeC-All Jobs by PT (Shen)	Score of accessibility to all jobs by public transport, taking travel time, number of jobs and competition for jobs into account (Shen, 1998)
NS-SeC-1 Jobs by PT (Shen)	Score of accessibility to higher professional and higher managerial and administrative jobs by public transport, taking travel time, number of jobs and competition for jobs into account (Shen, 1998)
NS-SeC-2 Jobs by PT (Shen)	Score of accessibility to higher technical, higher supervisory, lower professional and lower managerial and administrative jobs by public transport, taking travel time, number of jobs and competition for jobs into account (Shen, 1998)
NS-SeC-3 Jobs by PT (Shen)	Score of accessibility to intermediate jobs by public transport, taking travel time, number of jobs and competition for jobs into account (Shen, 1998)
NS-SeC-4 Jobs by PT (Shen)	Score of accessibility to jobs as employers in small organisations and as own account workers by public transport, taking travel time, number of jobs and competition for jobs into account (Shen, 1998)
NS-SeC-5 Jobs by PT (Shen)	Score of accessibility to lower technical and lower supervisory jobs by public transport, taking travel time, number of jobs and competition for jobs into account (Shen, 1998)
NS-SeC-6 Jobs by PT (Shen)	Score of accessibility to semi-routine jobs by public transport, taking travel time, number of jobs and competition for jobs into account (Shen, 1998)
NS-SeC-7 Jobs by PT (Shen)	Score of accessibility to routine jobs by public transport, taking travel time, number of jobs and competition for jobs into account (Shen, 1998)
NS-SeC-All Jobs by Car (Shen)	Score of accessibility to all jobs by car, taking travel time, number of jobs and competition for jobs into account (Shen, 1998)
NS-SeC-1 Jobs by Car (Shen)	Score of accessibility to higher professional and higher managerial and administrative jobs by car, taking travel time, number of jobs and competition for jobs into account (Shen, 1998)
NS-SeC-2 Jobs by Car (Shen)	Score of accessibility to higher technical, higher supervisory, lower professional and lower managerial and administrative jobs by car, taking travel time, number of jobs and competition for jobs into account (Shen, 1998)
NS-SeC-3 Jobs by Car (Shen)	Score of accessibility to intermediate jobs by car, taking travel time, number of jobs and competition for jobs into account (Shen, 1998)
NS-SeC-4 Jobs by Car (Shen)	Score of accessibility to jobs as employers in small organisations and as own account workers by car, taking travel time, number of jobs and competition for jobs into account (Shen, 1998)
NS-SeC-5 Jobs by Car (Shen)	Score of accessibility to lower technical and lower supervisory jobs by car, taking travel time, number of jobs and competition for jobs into account (Shen, 1998)
NS-SeC-6 Jobs by Car (Shen)	Score of accessibility to semi-routine jobs by car, taking travel time, number of jobs

	and competition for jobs into account (Shen, 1998)
NS-SeC-7 Jobs by Car (Shen)	Score of accessibility to routine jobs by car, taking travel time, number of jobs and competition for jobs into account (Shen, 1998)
Underground Road Distance	Road distance to nearest underground station from property
Underground Euclidean Distance	Euclidean distance to nearest underground station from property
Environmental attributes	
% Local Park Access	% of households within 400 m walking distance to a local, small and pocket park in the ward in 2011/12
% District Park Access	% of households within 1.2 km walking distance to a district park in the ward in 2011/12
% Metropolitan Park Access	% of households within 2.4 km walking distance to a metropolitan park in the ward in 2011/12
% Regional Park Access	% of households within 5 km walking distance to a regional park in the ward in 2011/12
% Nature Access Deficiency	% of households more than 1 km away from an accessible Site of Interest for Nature Conservation in the ward in 2011/12
% Greenspace	% of greenspace in land cover in the LSOA in 2011
% Water	% of water in land cover in the LSOA in 2011
% Road	% of road in land cover in the LSOA in 2011
% Railway	% of railway in land cover in the LSOA in 2011
% Building	% of building in land cover in the LSOA in 2011
% Structure	% of structure in land cover in the LSOA in 2011
NO_2	Annual average NO_2 concentrations at the property location in 2013 (ug/m^3)
NO_x	Annual average NO_x concentrations at the property location in 2013 (ug/m^3)
PM_{10}	Annual average PM10 concentrations at the property location in 2013 (ug/m^3)
Days PM_{10} 50	Number of days with a daily mean PM10 concentrations greater than 50 μg/m^3 at the property location in 2013
$PM_{2.5}$	Annual average PM2.5 concentrations at the property location in 2013 (ug/m^3)
Road Noise	Annual average road noise level at the property location in 2012 (L_{den})
Rail Noise	Annual average rail noise level at the property location in 2012 (L_{den})
Airport Noise	Heathrow Airport average 2011 summer day noise level at the property location (L_{Aeq})

Appendix 2. Hedonic price models for the full sample and the four submarkets, using ordinary least square regression.

Variable	Full sample		Submarket 1		Submarket 2		Submarket 3		Submarket 4	
	Coefficient	*t*	Coefficient	*t*	Coefficient	*t*	Coefficient	*t*	Coefficient	*t*
Constant	12.5128	329.39	12.0373	280.96	12.4318	648.03	12.8773	383.49	12.949	89.72
Detached House	0.9963	147.55	0.0765	2.01	0.1709	29.76	0.2199	42.06	0.6614	39.9
Semi-detached House	0.6984	160.57	0.1573	18.62	0.1403	53.22	0.1454	36.28	0.5175	37.21
Terraced House	0.5627	161.46	0.1496	29.65	0.0971	43.85	0.1237	38.48	0.4208	38.93
New-build	0.1903	27.03	0.073	7.73	0.0584	15.73	0.0412	7.72	0.1808	7.47
Neighbourhood Component 1	-0.0483	-20.13	0.0065*	1.84	-0.0046	-3.45	-0.0229	-11.89	-0.0792#	-10.17
Neighbourhood Component 2	-0.1679	-120.66	-0.0204	-9.57	-0.0324	-39.63	-0.0401	-34.46	-0.0968	-21.17
Neighbourhood Component 3	-0.1043	-77.54	-0.0198	-12.63	-0.0249	-34.14	-0.0148	-11.41	-0.0469	-8.21
Neighbourhood Component 4	0.0513	38.53	0.0092	5.34	0.0063	9.62	0.0158	13.28	0.0138	2.19
Neighbourhood Component 5	-0.2381	-164.06	-0.0208	-8.23	-0.0409	-43.72	-0.0512	-40.25	-0.1754	-38.45
Neighbourhood Component 6	-0.0446	-33.72	-0.0119	-5.63	-0.0101	-13.49	-0.0109	-10.85	-0.0253	-7.88
Neighbourhood Component 7	-0.0704	-44.15	-0.0096	-3.89	-0.0171	-18.79	-0.0207	-16.79	-0.0818	-17.79
Neighbourhood Component 8	0.0722	48.69	-0.0168	-6.18	-0.0069	-6.81	0.0093	8.24	0.0992	28.27
NS-SEC-2 Jobs by Car	0.0217	104.89	0.0021	6.46	0.0035	28.85	0.0039#	22.86	0.0165#	26.63
NS-SEC-2 Jobs by PT/Car	-0.2092	-6.53	0.0085*	0.19	-0.0311*	-1.76	-0.0521	-2.14	-0.7679	-8.66
% Nature Access Deficiency	-0.0008	-16.63	-0.0002	-3.04	-0.0001	-3.69	-0.0002	-5.3	-0.0006	-4.54
NOx	-0.0022	-15.25	-0.001	-4.62	-0.0003	-3.34	-0.0002	-2.13	-0.0035	-8.96
Road Noise	-0.003	-8.71	-0.0003*	-0.68	-0.0008	-4.48	-0.0006	-2.31	0.0033	3.08
Rail Noise	-0.0074	-11.16	-0.002	-2.82	-0.0013	-3.93	-0.0019	-3.13	-0.0024*	-0.91
Observations	85732		14610		33770		24471		12881	
R^2	0.639		0.093		0.169		0.153		0.317	
Adjusted R^2	0.639		0.092		0.168		0.152		0.316	
Log likelihood	-38760.7		2021.97		21792.2		10398.7		-6596.86	
Akaike info criterion	77559.3		-4005.93		-43546.3		-20759.3		13231.7	
Schwarz criterion	77737.1		-3861.73		-43386.2		-20605.3		13373.5	

* not significant at 0.05 level
\# 5 ≤ VIF < 10 (otherwise < 5)