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Transport Accessibility and Land Value – A Commercial property price model for Northern England

Daniel Johnson

Associate Professor

Institute for Transport Studies, University of Leeds

Dr. Like Jiang

Senior Research Fellow

Institute for Transport Studies, University of Leeds

Dr. John Nellthorp

Senior Research Fellow

Institute for Transport Studies, University of Leeds

Dr. Manuel Ojeda Cabral

Associate Professor

Institute for Transport Studies, University of Leeds

Abstract

The central aim of this study was to use newly-developed models to develop the evidence base on the relationship between transport accessibility and commercial property prices. Understanding commercial property impacts help understand the benefits following transport interventions and potential revenues from land value capture. In developing a set of hedonic models of commercial property value for the TfN area, we allowed for a detailed analysis of the role of accessibility, by multiple modes. Our models include business-to-business (B2B) accessibility, as well as business-to-labour (B2L) accessibility, to take into account important linkages between businesses as well as access to labour/customers. Our modelling results found significant impacts for floorspace, nearby tram stops, local area employment density, income and deprivation measures. For accessibility, the picture is more nuanced with different accessibility measures emerging as important for different property types.

1. Introduction

Land purchasers and users are prepared to pay more for land closer to CBD (Alonso 1964). Hedonic pricing models (Rosen, 1974) attribute land value variation across space to individual property characteristics and area level characteristics, amenities and accessibility. Rent gradients typically decline with distance from CBD, with interventions (including transport) leading to increases in the value of land

Accurate modelling of Land Value Uplift (LVU) allows us to understand beneficiaries from schemes, possibly to help scheme funding. Sometimes LVU used as a proxy for economic impact. In some areas, commercial (non-domestic) property makes up a large share of the total building stock.

With regard to the role of transport, there is a considerable body of research on residential property markets, eg see Zhang and Yen (2020) and Mohammad et al., (2013) for recent meta analyses of impacts of BRT and Rail schemes respectively). However, commercial property research is less developed, restricted as it is by fewer properties and transactions meaning less data is available (eg see Yu et al, 2016, Cervero and Duncan, 2002). Many LVU studies focus on proximity to transport hubs rather than gravity based accessibility measures for access to population or jobs. Understanding commercial property impacts help understand the benefits following transport interventions and potential revenues from land value capture.

The work described in this paper develops a model of commercial property value for the whole TfN area, at a fine level of spatial detail. We estimate a set of hedonic commercial models for the TfN area which explains estimated annual rateable value per square metre of commercial properties of four types: office, retail, industry and other, in terms of transport and non-transport accessibility measures, socioeconomic indicators and usage and floorspace.

We make a number of contributions to the literature in the area of commercial property market modelling.

- We include in our models a measure of business-to-business gravity based accessibility, as well as the more common home-to-business accessibility used in some residential models. Accessibility measures are estimated across all spatial zones with an impedance measure (GJT) and a deterrence function including a calibrated decay parameter. This is the first work of its kind to cover the impact of a range of accessibility measures, for different modes, on commercial property values.
- We also use spatial modelling approaches to address issues of spatial dependence in such models.

2. Methodology

2.1. Geographic scope and commercial property data

The geographic scope of this study covers the TfN area which comprises the North West, North East and Yorkshire and the Humber regions, and a subset of the East Midlands region (Bolsover, Chesterfield, Derbyshire Dales, NE Derbyshire and Bassetlaw local authorities). The area has a population of around 15 million according to Census 2011.

The commercial property data used in this study was from Valuation Office Agency's (VOA) Rating List Data (Gov.uk, 2020). The dataset contains estimated annual rateable value of each property, which is a measure of the property's open market rental value at the antecedent valuation date. The estimations are supported by regular site and building surveys or are based on construction costs or annual accounts (VOA, 2020).

The 2017 rating list (2015 value) was used as this was the most recent data available at the time of the study. In this list, total stock of commercial properties in the TfN area is 559,750 with a total rateable value of around £14 billion.

All types of commercial properties were relevant for the analysis, but the relationship with accessibility was expected to differ between different property types. Based on the

Primary Description Code in the VOA data, we classified the dataset into 4 subsets: Office, Retail, Industrial, and Other. Example properties and summary statistics of the 4 subsets are provided in Table 8.

2.2. Modelling strategy

The strategy involved the following aspects

- Four sets of models by property type (office, industrial, retail, other) to reflect different land uses, customer base and accessibility requirements of different commercial enterprises.
- A dependent variable measuring Log of value per m2;
- In accordance with hedonic pricing models the independent variables reflect accessibility, property characteristics, place quality and socio-economic characteristics
- Random effect (RE) models to capture effect of unobserved spatial heterogeneity (at MSOA level), supplemented by spatial regression models to examine the impact of spatial correlations on values.

The use of Semi-log functional form allowed for interpretation of percentage changes in property value per unit of change of explanatory variables, eg access to an extra worker. Models were estimated with robust standard errors estimated which takes into account impact of heteroscedasticity (conservative T-stats)

OLS models were estimated with clustered errors to deal with correlations of observations within MSOAs but RE models were better estimated and Breusch-Pagan tests showed these to be more appropriate.

2.3. Transport accessibility measures

We used gravity-based accessibility measures in this study:

$$\boldsymbol{A_{jm}} = \sum_{\boldsymbol{k}} \boldsymbol{N_k} \cdot \boldsymbol{f_m}(\boldsymbol{GJT_{jkm}})$$

where A_{jm} is the accessibility of the commercial property location j by mode m; N_k is the opportunity at location k, e.g., population, labour and other business depending on property type at location j (see below); GJT_{jkm} is the generalised journey time between locations j and k by mode m; and f_m is the deterrence function of GJT by mode m.

Whereas residential prices are based on accessibility to jobs and services from households, there are different accessibility requirements for commercial properties depending on types of business activity conducted there:

- Office – require access to/from staff, business to business travel and possibly deliveries and servicing.
- Industrial – requires staff accessibility, business travel, goods, and servicing.
- Retail – require staff and customer accessibility, goods and servicing.
- Other – range of activities not elsewhere covered including leisure, hospitality and social functions.

Therefore, alongside the accessibility to labour and population (B2L) measure, which is the inverse of the accessibility to jobs measure typically used in residential modelling, we included: accessibility to other businesses for passenger trips (B2B passenger), likely to be more prevalent in Sectors K and L of the UK Standard Industrial Classification (SIC)[1]; accessibility to other businesses for freight (B2B freight), for a range of sectors (C, F, G, H).

The deterrence function f_m is a cumulative probability function, based on data showing how people's willingness to travel varies with distance. For this study, we used various data to calibrate different deterrence functions depending on mode (rail, car and walk) and trip type (B2L and B2B passenger/freight). A summary of our accessibility measure components is listed in Table 1

Table 1. Accessibility measures components used in this study.

Mode	Property type	Trip type	Deterrence function	Calibration data	Destination opportunity*
Rail	Office; Retail; Industrial; Other	B2L	1-exp(-21993.7*GJT^-2.46129)	Trips by distance travelled to work, from 2011 Census	Population aged 15-64
		B2B	exp(-0.000003832*GJT^2.2146)	Rail business Trip Length Distributions, from NoRMS	No. of employments in SIC Sectors K and L
Car	Office; Retail; Other	B2L	1-EXP(-108.378*GJT^-1.88861)	Trips by distance travelled to work, from 2011 Census	Population aged 15-64
		B2B passenger	exp(-0.004795*GJT^1.269)	Road business Trip Length Distributions (TLDs), from Northern Highway Assignment Model (NoHAM)	No. of employments in SIC Sectors K and L
	Industrial	B2L	Same as for the other 3 types	-	Population aged 15-64
		B2B freight	EXP(-0.00002753645*GJT^1.8814)	Tonne-weighted trip length distributions, from Continuing Survey of Road Goods Transport (CSRGT)	No. of employments in SIC Sectors C, F, G and H
Walk	Office; Retail; Industrial; Other	B2L	1-EXP(-29.749*GJT^-1.33)	Trips by distance travelled to work, from 2011 Census	Population aged 15-64
		B2B			No. of employments in SIC Sectors K and L

*Population data was from 2011 Census; employment data was from Business Register and Employment Survey (BRES) for 2017.

Rail accessibility was calculated at the geographic scale of OA (origin) to LSOA (destination). While we only included origins within the TfN boundary, we expanded the boundary with a 50km buffer for destinations. Zone-to-zone journey time outputs was

[1] SIC Sector K: Financial and insurance activities; L: Real estate activities; C: Manufacturing; F: Construction; G: Wholesale and retail trade; repair of motor vehicles and motorcycles; H: Transportation and storage

obtained from TfN's Northern Rail Modelling System (NoRMS), covering: access/egress time; initial wait time; in-vehicle time; interchange time; delay time; and crowding penalty. Weights have been applied to elements of the journey times in accordance with the rail industry's Passenger Demand Forecasting Handbook (RDG, 2018). The original MSOA-based access and egress times from NoRMS were recalculated in GIS with OS Open Roads data to achieve the finer OA-LSOA scale.

Car accessibility was calculated at the geographic scale of MSOA (origin) to MSOA (destination). Road distance matrix was calculated in GIS using OS Open Roads data, with a cut-off distance of 150 km to reduce calculation. To convert distance to journey time, we assumed average car speed of 35.9 km/h for commute and 51.0 km/h for business trips, based on data from National Travel Survey (Tables nts0409, tsgb0111 and tsgb0112 for commute and ntsq99008 for business trips).

Walk accessibility was calculated using the same approach as for car accessibility, but at LSOA-LSOA scale with a cut-off distance of 10 km, and an assumed speed of 4.8 km/h.

2.4. Other explanatory variables

Other explanatory variables included property characteristics, place quality, and socio-economic variables. Property characteristics variables were obtained from the VOA data which included information such as floorspace and sub-category of usage (e.g., shop, restaurant, warehouse).

Place quality variables were mostly calculated by us in GIS, using property postcode locations from VOA data, and data of points of interest, greenspace, air pollution, noise, flood risk, etc, from various sources. Detailed descriptions can be found in Nellthorp et al. (2019).

Socio-economic variables were all at LSOA level, and included deprivation quartile dummies from the Index of Multiple Deprivation (IMD) 2017 data, average income from ONS PAYE/benefit estimates for 2015/16, population density from 2011 Census, and employment density (jobs per hectare) calculated using employment and area data for each MSOA.

2.5. Spatial regression

Spatial autocorrelation would normally be present in hedonic pricing studies (Jiang et al., 2021), and it was confirmed by Moran's I test for our datasets. Therefore, we conducted spatial regressions in GeoDa (Anselin et al., 2009) in addition to random effect models. We used K-Nearest Neighbor (KNN) for the construction of spatial weights, since Distance-Band weights would need very large minimum cut-off distances (>10km) to avoid isolations in our datasets.

Due to the very large sizes of our datasets and limited computer power, modelling settings we could test were limited. After testing spatial lag models (SAR) and spatial error models (SEM) with KNN10, KNN20, KNN25 and KNN50 weight matrices, and each with row-standardised weights and weights as a distance function ($1/d^2$) on the Other property type dataset, we decide to only run SAR and SEM with row-standardised KNN10 and KNN20 weight matrices for each property type, considering model fit and calculation time. Model fit was judged by choosing lowest Akaike's information criterion (AIC) (Stakhovych & Bijmolt, 2009).

3. Results

Table 2: Random effects model results

Variable name	Description	1- Other	2- Retail	3- Industry	4- Office
Empden	Employment density	0.00406**	0.001137**	0.000175	0.0012641**
Walk_Jobs_Disct	B2B Walk accessibility				0.0000145
Walk _Pop_Disct	B2L Walk accessibility		4.61E-07		
Rail_labour_Pop_Disct	B2L Rail accessibility	4.88E-07**	1.89E-07	-8.18E-08	
Car_Passenger_Pop_Disct	B2L Car accessibility	1.27E-07**			
Car_Passenger_Jobs_Disct	B2B Car accessibility				1.96E-06**
Freight_Job_G_Disct	Freight accessibility		1.05E-07**		
Freight_Job_C_Disct	Freight accessibility			1.47E-07**	
Supermarket_L_Distance_m	Distance to nearest supermarket		-2.66E-05**	-9.47E-06**	
Bank_1_distance_m	distance to nearest bank		-0.000044**	-2.57E-06	-1.09E-05**
Count_TramStop500m	Tram stops within 500m	0.0946**	0.0773**	0.0680**	0.0288*
Count_BusSTop500m	Bus stops within 500m		0.00724**		-0.00208**
NO2	NO2 concentration			0.0111**	0.0102**
flood_risk_high	Flood risk high				0.0612
income	LSOA HHIncome	1.32E-06**	8.64E-07*	-1.95E-07	-2.94E-07
imd50	IMD 25-50th %ile	0.0122	0.0819**	0.0127	0.0648**
imd75	IMD 50th-75th %ile	0.0413	0.154**	0.0385*	0.123**
imd100	IMD 75th-100th %ile (least deprived)	0.0632*	0.217**	0.0720**	0.218**
TotalArea	Floorspace (m2)	-8.6E-05**	-5.44E-05**	-8.38E-06	-3.11E-05**
comp_dum	residential/commercial	0.0716**	-0.0207**	-0.0919**	-0.0792**
unit_gia		-0.494**	-0.0641	0.3541**	0.0288
unit_nia		-0.520**	-0.353**	0.5742**	0.332**
Property type dummies not reported					
_cons		3.94**	4.70**	2.911**	3.56**
Observations		*77,292*	*159,909*	*173,783*	*129,732*
Groups (MSOAs)		*1,997*	*1,995*	*1,943*	*1,980*
R-squared		*0.657*	*0.1775*	*0.3916*	*0.2553*

Overall, as shown in Table 2, we find the significant control variables over all property types include:

- Total area (-ve impact)
- IMD (+ve with decreasing levels of deprivation)
- Number of tram stops within 500m (+ve impact, may be city based impact, less significant for Office)
- NO2 (+ve impact, proxy for built up area?)
- Employment density (+ve impact, except in Industry)
- Income (+ve impact for Other)

All these variables are of the expected sign except the counterintuitive NO2 results which suggest this variable may be acting as a proxy for a built up area.

In terms of the accessibility results we make the following observations from Table 2:

Other –

- Car B2L significant: Accessibility to 10,000 extra population increases commercial value by 0.127%
- Rail B2L significant - access to 10k population increases commercial value by 0.49%

Retail –

- ‘Freight’ distributed B2B in sector G (Wholesale and retail trade; repair of motor vehicles and motorcycles) signficant
- Accessibility to 10,000 extra employment in sector G increases commercial value by 0.105%

Industry –

- Freight distributed B2B significant for sector C (Manufacturing)
- Accessibility to 10,000 extra employment in the sector increases commercial value by 0.147%

Office –

- Car distributed B2B significant
- Accessibility to 10,000 extra jobs increases commercial value by 1.96%

Table 3 in the appendix compares the overall performance of the different RE and SEM (it is not straightforward to compare coefficients from SAR) models along with the size and precision of their respective accessibility estimates. Overall the SEM models have better measure of fit and the significance and size of the Lambda measure suggests there exists spatial correlation of the errors and the significance and size of the W variable suggests there is spatial lag evident in commercial property values between areas. Overall the SEM models tend to estimate the accessibility coefficients with more precision but similar magnitudes to the RE models.

Table 4 to Table 7 presents the full different spatial specifications for the different property types.

4. Conclusion

We have successfully estimated commercial property models which use GJT accessibility based on gravity models rather than usual distance based measures. Our approach more accurately reflect drivers of productivity and profitability which will be reflected in commercial property values. We offer detailed bespoke consideration of underlying accessibility functions (calibrated to available data, multiple modes, B2B, B2L, freight)

The resultant models suggest price premia for properties in denser, more affluent areas, with better transport access to firms/workers/customers/suppliers. The results have been taken forward by TfN in their Wider Economic Impacts calculation tool for appraisal of potential schemes. Results are robust to different spatial specifications.

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Appendix

Table 3: Model Results comparison

Variable name	1- Other			2- Retail			3- Industry			4- Office		
	REM	SEM 10	SEM 20	REM	SEM 10	SEM 20	REM	SEM 10	SEM 20	REM	SEM 10	SEM 20
Walk_Jobs_Disct										1.45E-05	2.48E-05**	2.34E-05**
Walk _Pop_Disct				4.61E-07	1.45E-06**	1.48E-06**						
Rail_labour_Pop_Disct	4.88E-07**	3.24E-07**	2.94E-07**	1.89E-07	1.09E-07**	9.42E-08**	-8.18E-08	-1.33E-07**	-1.03E-07**			
Car_Passenger_Pop_Disct	1.27E-07**	2.44E-07**	2.98E-07**									
Car_Passenger_Jobs_Disct										1.96E-06**	1.18E-06**	1.12E-06**
Freight_Job_G_Disct				1.05E-07**	9.96E-08**	1.14E-07**						
Freight_Job_C_Disct							1.47E-07**	9.96E-08**	1.03E-07**			
R-squared	*0.657*	0.735	0.732	*0.178*	0.515	0.505	*0.392*	0.628	0.615	*0.255*	0.662	0.641

Table 4: Spatial Model Results for Type 1 properties (Other)

Type 1	SEM				SAR			
	KNN10		KNN20		KNN10		KNN20	
R2	0.734619		0.732092		0.692258		0.689356	
AIC	172863		172696		181466		181908	
Variable	Coefficient	z-value	Coefficient	z-value	Coefficient	z-value	Coefficient	z-value
CONSTANT	3.99245	202.78	3.98716	169.49	2.65102	131.86	2.51818	118.07
Car_Passen	2.44E-07	5.83	2.98E-07	5.54	4.05E-07	21.89	4.35E-07	23.37
Count_Tram	0.039723	3.45	0.05306	4.11	-0.03624	-6.74	-0.04291	-7.93
Rail_labou	3.24E-07	5.09	2.94E-07	4.34	9.85E-08	3.16	7.77E-08	2.48
TotalArea	-7.18E-05	-33.19	-7.04E-05	-32.41	-8.85E-05	-38.43	-8.82E-05	-38.10
imd50	-0.02125	-1.67	-0.01972	-1.59	-0.02021	-2.38	-0.01995	-2.33
imd75	0.003692	0.26	0.017031	1.21	-0.03812	-4.48	-0.03863	-4.52
imd100	0.035669	2.26	0.028281	1.76	0.01292	1.46	0.007093	0.80
comp_dum	0.132209	14.97	0.134899	15.18	-0.00643	-0.71	-0.00285	-0.31
holiday	2.42884	186.70	2.42691	185.77	2.04691	154.15	2.03942	151.81
car_park	1.46361	126.49	1.46814	127.43	1.20991	107.13	1.21995	107.64
hall	-0.55152	-54.16	-0.55549	-54.35	-0.76102	-72.45	-0.76263	-72.23
misc_leis	0.744953	64.62	0.743509	64.35	0.618779	51.30	0.624407	51.53
comm	0.889833	1.80	0.967493	1.93	0.632981	1.17	0.695025	1.28
pub	0.587959	10.06	0.553869	9.41	0.349484	5.51	0.337911	5.30
advert	2.14867	60.03	2.15295	60.14	2.02795	53.49	2.04001	53.56
restaurant	0.934387	87.27	0.950464	88.91	0.738599	68.98	0.747414	69.49
school	0.404307	2.07	0.401389	2.04	0.18753	0.88	0.158811	0.74
surgery	0.833537	65.81	0.830512	65.57	0.586442	44.46	0.590862	44.59
cafe	0.882027	73.27	0.885012	73.24	0.633373	50.44	0.633658	50.20
club	1.464	6.82	1.5556	7.68	1.449	7.31	1.49642	7.51
nursery	0.699893	53.26	0.683241	51.77	0.465212	33.35	0.460158	32.83
ground	-0.37029	-20.44	-0.36777	-20.20	-0.52361	-27.01	-0.52645	-27.03
unit_gia	-0.50075	-50.67	-0.4961	-50.24	-0.41065	-40.71	-0.41113	-40.56
unit_nia	-0.57018	-55.94	-0.56677	-55.74	-0.43551	-42.46	-0.4361	-42.32
empden	0.00337	21.63	0.002492	14.21	0.002342	31.24	0.002182	28.85
income	6.68E-07	3.60	7.48E-07	4.21	1.02E-06	8.59	1.06E-06	8.86
LAMBDA	0.642592	145.23	0.744307	152.96				
W_lnValpersm					0.322418	0.00	87.953	0.35

Table 5: Spatial Model Results for Type 2 properties (Retail)

Type 2	SEM				SAR			
	KNN10		KNN20		KNN10		KNN20	
R2	0.515097		0.504782		0.513218		0.508793	
AIC	226409		225950		226157		220740	
Variable	Coefficient	z-value	Coefficient	z-value	Coefficient	z-value	Coefficient	z-value
CONSTANT	4.78481	121.96	4.78775	113.77	1.65486	45.33	1.32565	35.90
Car_Freigh	9.96E-08	5.98	1.14E-07	5.19	1.86E-08	3.77	1.56E-08	3.16
Walk_PopAg	1.45E-06	4.82	1.48E-06	3.69	5.94E-07	7.36	4.40E-07	5.42
Supermarke	-2.81E-05	-8.65	-3.82E-05	-12.40	-6.67E-06	-5.99	-9.87E-06	-8.82
Bank_1_dis	-3.94E-05	-12.62	-2.61E-05	-8.37	-1.67E-05	-17.57	-1.40E-05	-14.70
Count_Tram	0.059984	7.56	0.053612	6.01	0.015017	6.39	0.012106	4.96
Count_BusS	0.004764	15.01	0.004219	12.24	0.001738	16.98	0.00135	13.12
Rail_labou	1.09E-07	2.65	9.42E-08	2.09	3.04E-08	2.47	1.78E-08	1.43
TotalArea	-6.55E-05	-40.31	-6.14E-05	-37.60	-5.93E-05	-37.68	-5.77E-05	-36.45
imd50	0.085585	11.61	0.062256	9.01	0.030224	9.56	0.023758	7.47
imd75	0.163468	18.46	0.117191	13.73	0.07049	19.48	0.053895	14.75
imd100	0.269649	24.65	0.178811	16.88	0.133218	30.67	0.104558	23.84
comp_dum	0.053646	13.72	0.041362	10.46	0.019968	5.22	0.017729	4.60
shop	-0.15077	-26.05	-0.15941	-27.16	-0.15459	-26.72	-0.16131	-27.75
salon	-0.13632	-17.85	-0.14996	-19.33	-0.15792	-20.58	-0.16524	-21.44
warehouse	-0.09103	-6.65	-0.06462	-4.92	-0.11675	-10.63	-0.09713	-8.79
showroom	-0.70546	-65.50	-0.71902	-66.56	-0.68546	-66.92	-0.6985	-67.75
unit_gia	-0.23232	-6.64	-0.19716	-5.58	-0.17231	-4.93	-0.15723	-4.46
unit_nia	-0.42207	-12.29	-0.39616	-11.44	-0.39956	-11.61	-0.37352	-10.75
empden	0.001613	13.03	0.001334	9.99	0.000436	10.83	0.000298	7.37
income	4.29E-07	1.35	1.05E-06	3.47	-1.15E-07	-0.92	-2.25E-08	-0.18
car_inc	-4.40E-12	-1.63	-6.94E-12	-2.69	6.36E-13	0.58	2.80E-13	0.26
LAMBDA	0.751528	344.38	0.827679	364.09				
W_lnValpersm					0.733603	329.20	0.807885	343.84

Table 6: Spatial Model Results for Type 3 properties (Industry)

Type 3	SEM				SAR			
	KNN10		KNN20		KNN10		KNN20	
R2	0.627938		0.615441		0.587547		0.580394	
AIC	178466		180271		191892		192516	
Variable	Coefficient	z-value	Coefficient	z-value	Coefficient	z-value	Coefficient	z-value
CONSTANT	2.80513	157.53	2.82412	134.86	0.999122	92.61	0.737935	67.50
Car_Freigh	9.96E-08	6.15	1.03E-07	4.74	1.78E-08	3.79	1.15E-08	2.42
Supermarke	-8.64E-06	-3.78	-1.11E-05	-4.59	-7.79E-07	-1.03	-1.10E-06	-1.44
Bank_1_dis	-6.39E-06	-2.92	-7.64E-06	-3.21	2.86E-06	4.04	4.05E-06	5.65
Count_Tram	0.0304281	3.66	0.037248	4.41	0.007013	2.31	0.005258	1.72
NO2	0.014095	17.18	0.013184	14.28	0.007777	27.93	0.006822	24.28
Rail_labou	-1.33E-07	-4.14	-1.03E-07	-2.93	-6.96E-08	-6.45	-6.63E-08	-6.09
TotalArea	-1.21E-05	-60.06	-1.26E-05	-61.34	-5.68E-06	-34.60	-5.61E-06	-33.60
imd50	0.036948	5.61	0.014501	2.28	0.02346	8.47	0.020672	7.40
imd75	0.0555963	7.17	0.026341	3.45	0.041476	12.88	0.035095	10.81
imd100	0.091531	10.17	0.053071	5.94	0.069208	19.10	0.057657	15.78
comp_dum	-0.0417684	-5.44	-0.05254	-6.75	-0.07616	-9.68	-0.0838	-10.56
i_warehous	0.0388942	6.86	0.034156	5.94	0.021027	3.82	0.026272	4.73
i_workshop	0.108505	19.61	0.10332	18.40	0.073306	13.62	0.082783	15.25
i_store	0.106704	17.70	0.090325	14.76	0.056736	9.94	0.06315	10.97
i_factory	-0.138303	-20.48	-0.14886	-21.71	-0.16587	-24.85	-0.16773	-24.91
i_storage	-1.3939	-165.16	-1.39268	-161.01	-1.48251	-191.58	-1.48882	-191.20
i_vrep	0.172681	24.29	0.155115	21.46	0.12915	18.07	0.131433	18.23
unit_gia	0.406653	54.01	0.429051	54.66	0.189574	36.68	0.196683	37.65
unit_nia	0.573541	54.85	0.591739	55.36	0.340272	40.89	0.345129	41.06
empden	-0.000169116	-1.46	-0.0001	-0.83	-0.00037	-9.04	-0.00042	-10.21
income	-7.15E-08	-0.65	-9.88E-08	-0.98	-1.51E-07	-2.80	-1.40E-07	-2.58
i_garage	0.119617	14.23	0.100105	11.70	0.054676	6.40	0.058398	6.77
LAMBDA	0.736212	336.35	0.807664	346.77				
W_lnValpersm					0.626184	305.64	0.704217	331.63

Table 7: Spatial Model Results for Type 4 properties (Office)

Type 4	SEM				SAR			
	KNN10		KNN20		KNN10		KNN20	
R2	0.66214		0.640585		0.65946		0.637328	
AIC	30545.3		34119.8		30837.5		34664.2	
Variable	Coefficient	z-value	Coefficient	z-value	Coefficient	z-value	Coefficient	z-value
CONSTANT	3.75292	131.58	3.70573	119.96	0.49279	20.195	0.257674	10.2296
Car_Passen	1.18E-06	10.994	1.12E-06	7.4513	2.42E-07	11.446	1.77E-07	8.14281
Walk_SIC7_	2.48E-05	15.266	2.34E-05	11.748	4.29E-06	12.016	3.27E-06	8.86479
Bank_1_dis	-2.14E-05	-13.39	-2.11E-05	-14.82	-2.26E-06	-4.393	-2.96E-06	-5.56917
Count_Tram	-0.00333299	-0.666	-0.001999	-0.362	0.00093	0.7905	0.000391	0.322916
Count_BusS	-0.00174465	-7.974	-0.000947	-4.189	-0.00061	-10.75	-0.00052	-8.80022
NO2	0.0091415	10.975	0.0110959	12.393	0.00306	14.558	0.002661	12.2462
flood_risk	-0.00183134	-0.16	0.004384	0.4339	0.0028	0.4708	0.005165	0.842087
TotalArea	-2.97E-05	-32.34	-3.07E-05	-32.45	-2.69E-05	-30.11	-2.81E-05	-30.5306
imd50	0.0437825	7.8477	0.0335008	6.4196	0.02078	9.6946	0.017771	8.03151
imd75	0.0956869	14.6	0.0706767	11.272	0.03885	16.519	0.031241	12.8554
imd100	0.159315	21.28	0.118106	16.342	0.07015	27.396	0.057102	21.524
comp_dum	-0.0244601	-3.923	-0.034714	-5.434	-0.0484	-7.973	-0.05731	-9.14824
unit_gia	0.0857536	3.5101	0.110286	4.3959	0.09982	4.2935	0.113667	4.73768
unit_nia	0.349327	14.494	0.379206	15.309	0.30277	13.164	0.331942	13.9847
empden	0.00022085	2.7421	-3.02E-05	-0.354	5.73E-05	2.7997	1.09E-05	0.518157
income	-1.12E-07	-1.539	-2.55E-08	-0.368	-5.38E-08	-2.327	-2.84E-08	-1.19018
LAMBDA	0.814577	414.43	0.869248	430.3				
W_lnValpersm					0.80028	399.93	0.851757	408.306

Table 8: Example property types and mean values

Property type	***Examples***	***Mean value per sq/m***
Other	Holiday homes/parks/hotels, car parks, pubs, leisure centres/sports grounds, Cafes/ Restaurant, Schools/Nurseries	£96.02
Retail	shops, salons, showroom	£98.10
Industry	warehouse, workshops, factories, storage facilities, garages	£32.07
Office	Offices	£85.62