Article:

Clark, S orcid.org/0000-0003-4090-6002, Hood, N orcid.org/0000-0002-2084-2155 and Birkin, M orcid.org/0000-0001-5991-098X (2021) A hedonic model of the association between grocery brand provision and residential rental prices in England. International Journal of Housing Markets and Analysis, 14 (4). pp. 680-700. ISSN 1753-8270

https://doi.org/10.1108/IJHMA-05-2020-0062

A hedonic model of the association between grocery brand provision and residential rental prices in England.

Dr Stephen Clark*, School of Geography, University of Leeds, LEEDS, LS2 9JT. tra6sdc@leeds.ac.uk

Dr Nicholas Hood, School of Geography, University of Leeds, LEEDS, LS2 9JT. N.A.Hood@leeds.ac.uk

Professor Mark Birkin, Leeds Institute for Data Analytics, University of Leeds, LS2 9JT. M.H.Birkin@leeds.ac.uk

*Corresponding author

Abstract

Purpose – This study measures the association between local retail grocery provision and private residential rental prices in England. Renting is an important sector of the housing market in England and local grocery provision is an important aspect of service provision and consumers are known to be highly sensitive to the branding of this type of retailing.

Design/methodology/approach – This research uses a novel data source from a property rental web platform to estimate a hedonic model for the rental market. These models incorporate information on the nature of the properties and their neighbourhoods, with an emphasis on how different retail brands are associated with rental prices. This retail brand is captured on two scales, the provision of local branded convenience stores and the provision of larger stores.

Findings – The study finds clear differentials in how the local grocery brand is associated with rental prices. When controlling for commonly explored confounding factors, 'Luxury' retailers such as Waitrose and Marks and Spencer are associated with higher rental prices, whilst 'Discounter' retailers are associated with lower rental prices. This finding has many implications, particularly in relation to potential price changes in an already challenging housing market for many people.

Originality – The focus of this research is on the private residential property market, an important market in England but one that has enjoyed less scrutiny than the sales or socially rented markets. Rather than using general accessibility to retail, this research has differentiated the association by the retail brand and store size, two very important aspects of consumer choice.

Research limitations/implications – This is an observational study and as such only associations (not causation) can be implied by these findings.

1 Introduction

In their article, Jang and Kang (2015) comment that retail activities are important functions of (urban) life which can play a role in shaping neighbourhood desirability and therefore rental and house prices. These economic positives resulting from greater retail provision and accessibility can be seen in urban growth and development (Glaeser et al., 2001) as provision attracts other businesses and customers into an area. Time savings (through convenience), increased choice (e.g. in a shopping centre or grocery hypermarket) or lower costs (through choice or economies of scale achieved by large retailers) are all possible with an increase in provision or improvement in access.

In the context of the United Kingdom (UK) housing market, numerous newspaper stories exalt the influence of major grocery retailers on UK house prices (for example see: Shaw (2017) and Burridge (2018)). They often centre on the idea of a 'Waitrose Effect', named after the luxury supermarket chain Waitrose, which is often said to have the largest effect on house prices of any major UK grocery retailer

(Lloyds Bank, 2017). However, these studies either inappropriately define the neighbourhood of a store and, of great concern in terms of the house price literature, attribute the entire premium associated with house prices to the retail effect, not controlling for other structural and locational factors. As we shall demonstrate here, this tends to over inflate the premium associated with retail and is the primary motivation for us to conduct this analysis.

Testing the impact of grocery supply on house prices contributes to the understanding of proximal effects of differential access to services and amenities at a local level. Several externalities have been found to be capitalised in house prices, ranging from positive factors such as access to good schools to negative impacts such as noise nuisance from busy roads. Whilst multiple studies have investigated the impact of access to retail services on house prices, the focus has generally been on access to central city / town shopping locations or on out-of-town shopping centres. A smaller subset of studies has focused on the impact of grocery supply on the housing market, but there is a dearth of such literature in a UK context and in terms of the variability of the grocery supply. Whilst the retail market is quite diverse in the UK, ranging from "Discounters", through the "Big-Four" retail chains and onto more niche "Luxury" retailers this diversity is rarely captured within these studies. Furthermore, previous studies on the impact on proximal grocery externalities on the housing market have focused almost exclusively on the home ownership sales submarket. . However there are two other substantive housing submarkets, social rented (where provision and rental is largely proscribed by legislation (Walker and Marsh, 2003, Wilson, 2019)) and the private rental market. This study addresses the gap in knowledge concerning the private rental submarket by using a hedonic modelling approach to assess the association between local grocery store brand and size and private rental prices in England. In doing so, it provides a tool that allows a guide price for rental properties to be estimated based on a range of factors.

This article proceeds as follows. Section 2 reviews and gives a brief overview of the literature on hedonic house price modelling, whilst section 3 focuses on studies relating to retail and house / rental price association. Section 1 discusses the data used, followed by the methodology in section 5. The paper is rounded off with the results in section 6 and discussion in section 7.

2 Hedonic house price modelling

Commonly, studies of house price capitalisation are focused on the sales market and adopt a hedonic approach (Rosen, 1974), with fewer studies focused on the rental market. There is some consensus in the literature that the housing market may not be monotonic and various studies have filtered the housing market into different subsets, known as submarkets, to better understand the drivers of house prices. Whilst the existence of such submarkets is generally uncontested, there is not an agreed definition of housing submarkets and how to identify them (Bangura and Lee, 2020). The private rental sector is an important segment of the UK housing market which has received little attention in the house price literature. Such properties accounted for around 17% of tenures in England at the most recent census

(2011), a figure found to have increased in subsequent years (Wilcox et al., 2017). This is a portion of the housing market worthy of further investigation.

Whilst this study focuses on the capitalisation of access to grocery stores in rental prices, other housing characteristics are commonly used in house price research (Wilkinson and Archer, 1973). Firstly, there are the structural aspects of the property in terms of its age, type and size, either captured as a square area or as a count of the number of rooms. In an international context, floor area was used in rental models for Tokyo (Hoshino and Kuriyama, 2009), Belfast (McCluskey et al., 2013) and Zurich (Löchl, 2010), and the number of rooms for studies in Zurich (Heng et al., 1997), Dhaka City (Ahmed et al., 2014), Belfast (McCord et al., 2014) and Haifa (Baron and Kaplan, 2010).

Whilst there is generally consensus over the specification of structural attributes in house price models, locational attributes garner greater debate and are diverse and inconsistent in their choice and measurement (Xiao et al., 2016). The monocentric urban model that proposes a decrease in house prices moving away from the Central Business District (CBD) has underpinned much of the hedonic house price literature (Orford, 2017). This has generally been superseded by studies recognising an array of locational externalities that have an impact on house prices across varying spatial scales, with several proximal factors found to influence demand for housing (for example, see Orford (2002)).

At an immediately local scale, the nature of the neighbourhood of the property has been studied in terms of its character (Heng et al., 1997, Baron and Kaplan, 2010, Kain and Quigley, 1970) or security, vis-a-vis crime (McCord et al., 2014, Oduwole and Eze, 2013). Of greater complexity in measuring accessibility, local services and amenities are also incorporated into models, such as the distance or quality of local schools (Zheng et al., 2016, McCord et al., 2014), local parks (Hoshino and Kuriyama, 2009, Del Giudice et al., 2017), or access to transport systems (Dubé et al. (2018), Gibbons and Machin (2005), Bohman and Nilsson (2016)). Given that the above structural and locational attributes are commonly found to have an influence on rental prices, it is important that these attributes are included as covariates in this paper

Several concepts related to spatial configuration / topography have been used in measures of accessibility to these locational externalities, particularly in relation to access to available employment (building on the monocentric urban model). (Waddell et al., 1993) suggest including both distance to CBD and distance to secondary employment centres. Other studies have found network accessibility such as gravity-based accessibility to various opportunities is a predictor of house prices (e.g. Adair et al. (2000)). Space syntax theory has also been applied in several studies, particularly in relation to street-network morphology and its effect on house prices (Xiao et al. (2016), Law (2017)). Choice of measures of accessibility apply to access to a variety of amenities, including those related to retail.

3 Retail externalities in house price modelling

A study by Song and Sohn (2007) of house prices in Oregon found that greater spatial accessibility to retail opportunities was capitalised in house prices among single-family home buyers. The scale and diversity of provision is also important, with a locally focused study of shopping centres in Florida, Sirpal (1994) finding that larger shopping centres had a greater impact on house prices than smaller shopping centres. This was corroborated in a larger scale study by Des Rosiers et al. (1996) who found that community sized shopping centres were associated with a far smaller premium in house prices than regional sized shopping centres. Outside North America, a European study by Stadelmann (2010) found that distance to shopping centre was negatively associated with house prices in Zurich, Switzerland, and a study in Nigeria (Aliyu et al., 2011) found shopping centres reduced house prices within 1500 feet, but increased prices beyond this distance. Law (2017) found a small but significant positive association between the number of stores (any retail sector) and house prices in London.

In a non-house price study but which is still relevant to the issues here, Clarke et al. (2006) found that convenience and/or location were the greatest drivers for people shopping at a given grocery store, suggesting that local grocery externalities are very important in people's lives and could therefore be expected be capitalised in prices. This effect was confirmed by (Kang, 2018) who found access to hypermarkets was positively associated with house prices up to a certain distance, suggesting ease of access to groceries is valued by consumers. Furthermore, a small positive association between 7/11 style convenience grocery stores and house prices at a distance of 100m was found in Taipei Metropolis (Chiang et al., 2015). Cerrato Caceres and Geoghegan (2017) charted the opening of 12 large grocery stores in Massachusetts, North America, from 1988-2011 and found that access to groceries increased house prices by about 7% within a 0-400m radius of the stores, and by 4% in a 400-800m band. Pope and Pope (2015) found that the presence of a Walmart store (in a study of several US states) benefitted house prices by 2-3% within 0.5 miles and by 1-2% within a 0.5-1 mile radius. Other literature on the positives/negatives of grocery store location for consumers has focused on the negatives resulting from a dearth of access in what is known as the food deserts debate (Walker et al., 2010).

Zentes et al. (2017), chapter 11, also highlights that some retailers account for housing variables in their location strategy, specifically noting housing age, type, density and ownership levels as location influencing factors in store retailing. For example, large grocery retailers are more likely than smaller grocery retailers to favour CBD locations (Hood et al., 2015). This is important in the context of this study as many of these decisions are informed by geographic variations in factors also known to influence property prices. The grocery market is dynamic and changes in the supply occur frequently, providing opportunities for private rental landlords to adjust prices based on the demand for access to this type of amenity.

Location planning teams often make use of composite indicators of variations in neighbourhood population characteristics, known in the location planning industry as geodemographic systems (Birkin et al., 2017). These characteristics can be demographic, economic or behavioural. The classification generally gives a label (e.g. 'prospering suburbs') to each neighbourhood and grocery retailers are known to profile potential customer bases and inform their store location strategy with the help of these systems. Previous research has found a link between area socio-economics and affinity with different retailers (Pechey and Monsivais, 2015). Thompson et al. (2012) used Acxiom's research opinion poll data to look at the variation in retailer representation by the type of area in which the respondent lived. Table 1 summarises the levels of over- and under-representation in the major UK grocery retail brands against geodemographic groups in the 2001 Census Output Area Classification (OAC) of UK neighbourhoods (Vickers and Rees, 2007). In this paper we control for such neighbourhood characteristics in order to isolate the association of the grocery stores with rental prices.

Table 1 : Customer base by retailer. Adapted from (Thompson et al., 2012)

This paper contributes to the literature in multiple ways. First, we focus on the private rental submarket in England, an area which has received comparatively little attention in the house price literature. In doing so, the main aim of the paper is to measure the association of rental prices and access to grocery amenities, measured both in terms of variation by size and brand, filling a gap in the existing literature. In doing so, factors known to be considered in the location strategy of grocery retailers and structural and locational factors previously found to influence house prices are controlled for. Finally, it provides a tool that allows a guide priced for rental properties to be established based on a range of factors.

4 Rental, Retail and Context Data

4.1 Rental Data

The rental data in this study is taken from the on-line property listings web site Zoopla (Zoopla, 2018), provided by the data services company WhenFresh (WhenFresh, 2018) and is restricted to properties for rent in England. Whilst the data covers the calendar years 2014 and 2015, only rentals from July 2014 to December 2015 are used for comparability with the 2015 retail data. These data are curated through the Consumer Data Research Centre at Leeds University, and are available subject to an open access Research Approvals Process (Consumer Data Research Centre, 2019). The property rental price is listed in pounds (£), per property, per week. In this study, properties that are listed at a price fewer than £25 (unlikely to be genuine) or greater than £5000 (an atypical segment of the market) are removed. This filtering removes 8,878 (0.8%) of the 1,111,600 unique property listings. These data also contains information on property type (detached, semi-detached, terraced, flat (apartment) and unknown), number of bedrooms (coded here as 1, 2, 3, 4, 5, 6+ and unknown), number of bathrooms (1, 2, 3, 4+ and unknown) and number of reception rooms (1, 2, 3, 4+ and unknown). The count of rooms are converted to categories so that the relationship with rental price can be non-linear whilst the use of an unknown category allows for both predictions to be made when this information is incomplete and to retain the observation for use in model estimation.

4.2 Retail Data

The retail data are taken from Geolytix (Geolytix, 2018a) who provide data from November 2014 on the location of retail stores in the United Kingdom (Geolytix, 2018b). Only stores from the major retailers, Aldi, ASDA, the Co-operative Group, Lidl, Marks and Spencer (M&S), Morrison's, Tesco, Sainsbury and Waitrose that were open during 2015 are used in this study. Together, these stores represented 93.3% of the Great Britain grocery retail market in 2015 (O'Reilly, 2015). Each store is categorised as a small store (fewer than $280m^2$), a small to medium store ($280m^2$ to $1,400m^2$), a medium to large store ($1,400m^2$ to $2,800m^2$), or large store (greater than $2,800m^2$). In this study the local convenience retail provision for a property is captured as the nearest small store brand within 500m (with an option of no small store), and the major retail provision as the nearest medium or large brand store (irrespective of distance). This distinction is important since trading restrictions are in place for medium to large stores that limit Sunday opening times.

4.3 Other Contextual Data

Other data are used to further control for the potential relationship between house rental prices and the retail provision. They are: (1) the distance of the property from London (measured as a distance in km's east/west and north/south of West London), this distance is logged to reflect that the impact is greater the closer to West London. (2) Several complementary area classifications. First the ACORN Category of the property's postcode (CACI, 2018), which primarily measures affluence of an area. Secondly the classification of the 2011 Census Output Area (OA) in which the property is located (Gale et al., 2016) which summaries the socio-demographic nature of the area. The final classification is an urban/rural classification of this OA (Office for National Statistics, 2013). (3) The 2015 estimated household income of the lower level super output area (LSOA) in which the property is located (Office for National Statistics, 2018). (4) A pair of accessibility indicators, the distance to the closest large employment centre (an LSOA with 5,000 or more jobs, Department for Transport (2015)) and the distance to the closest railway or London underground station (Department for Transport, 2017). (5) The quality of the local Primary and Secondary schools assessed through their OFSTED ratings (Baxter and Clarke, 2013). Finally (6) the "healthiness" of the local environment, in terms of its (a) non-grocery retail provision (e.g. poor health is associated with gambling and fast food establishments), (b) the availability of health services and (c) the environment (measured through air quality and green spaces)(Green et al., 2018).

The supplementary figures S1 to S19 illustrate the relationship between the logarithm of the rental listings price and these categorical factors and continuous measures.

4.4 Context based filtering

The property listing data is derived from a commercial data source and requires some "sense-checking" before it can be used for research. This task is not uncommon in the use of novel big data for research (Cai and Zhu, 2015). Initially, 0.8% of these data are removed by the adoption of the fixed price thresholds. Additionally, one context-based filtering rule is applied that further filters the data, and another corrects for a misspecification. For these filterings these data are divided into sub-sets, where each sub-set contains properties of the same type, the same number of bedrooms and all have postcodes with the same ACORN Group code. This ensures that when attempting to identify if a property listing makes sense, only comparable properties are used. The filtering is then applied in turn to each sub-set that contains at least 40 properties, to ensure that any summary statistics used are reliable.

For the first filtering, properties whose listing prices is less than 1.5 times the inter-quartile range below the lower quartile or more than 2.0 times the inter-quartile range above the upper quartile for the sub-set are identified and trimmed. This definition of an outlier is similar to the definitions of outliers used in box-plots (and McCord et al. (2014) eliminated properties based on a similar ±3 standard deviations rule).

The second filtering is more significant and relates to a mis-specification in the data. Examination of the listing prices identifies some properties, mainly in student areas, where the listing is on a per room, rather than a per property basis. In effect this provides two definitions for our response variable, which leads to modelling difficulties. The solution is to identify those properties which are listed per room and remove them. This is done by hypothesising that within each of the sub-set consisting of larger properties (3 or more bedrooms), there is a mixture of two Gaussian distributions. If the means of these two distributions are sufficiently different and one distribution is more numerous than the other, then the smaller distribution is separated out. The Mclust package (Scrucca et al., 2016) in R (R Core Team, 2016) is used to estimate the parameters of the two distributions. Figure 1 illustrates this in the context of terraced type properties, with five bedrooms, and in the ACORN Group 'Student'. Here properties in Class 1 are clearly those listed per bedroom and should be removed.

Figure 1 : Distribution of listing prices for five bedroom terraced properties

The cumulative impact of these context based filtering's are illustrated with reference to properties listed for rent in the Hyde Park area of Leeds, a neighbourhood with a large student population. Figure 2a shows this distribution for the original data, based on 1,423 properties. There are clearly outlying rents for properties with 1, 2, 3 and 6 or more bedrooms. After these properties have been trimmed the distribution looks much more compact as shown in Figure 2b, reducing the number of properties to 1,416, but the presence of untypically low rents is still apparent for 3, 4, 5 and 6 or more bedrooms. The plots after the separation out of the two distributions are shown in Figure 2c, leaving 1,096 properties. Whilst this latter process is not perfect, it has significantly reduced the number of properties that are listed on a per room basis.

Figure 2 : Distribution of rental listing price in Hyde Park, Leeds, by the number of bedrooms (a) Original data; (b) Trimmed data; (c) Segregated data

Whilst for Hyde Park the impact of these two filtering exercise has been fairly substantial (a 23% reduction), in total the trimming exercise reduces the number of properties by a modest 2.4% and the separation out of per room rental properties reduces the number of properties by a further 0.6%.

5 Methods and Model Estimation

To explore the relationship between the rental listing price and the retail provision a hedonic regression approach is used (Rosen, 1974). Using this approach, we can control for neighbourhood characteristics in order to isolate the association of the grocery stores with rental prices.

The distribution of the listing price is positively skewed suggesting a Poisson formulation of a generalised linear model. To allow for over-dispersion a quasi-Poisson formulation is adopted (Fox, 2015, Zuur et al., 2009). It is also likely that the standard errors will be clustered, with geographically close properties having similar characteristics and neighbourhood features. This will tend to under-estimate the standard errors of the parameters. One approach to account for this is to estimate models with cluster robust standard errors (Cameron and Miller, 2015) using the glm.cluster function in the R package miceadds (Robitzsch and Grund, 2020).

The full specification for the model is given in equation 1.

$$\log(E[R_i]) = \log(r_i) = \eta_i = \alpha + \beta_1 X_{i1} + \beta_2 X_{i2} + \cdots + \beta_k X_{ik} + \epsilon_i \quad (1)$$

$$Var(R_i|\eta_i) = \phi\, \eta_i$$

$$E[\epsilon_i \epsilon_j] = 0\ if\ i\ and\ j\ in\ different\ clusters$$

$$E[\epsilon_i \epsilon_j] \neq 0\ if\ i\ and\ j\ in\ same\ cluster$$

Where R_i is the observed rent for property i (£);
r_i is the modelled rent for property i (£);
η_i is the logarithm of the modelled rent for property i (log £);
X_{ik} are the k explanatory terms;
β_k are the k parameter estimates;
ϵ_i are model errors for property i; and
ϕ is a measure of under dispersion

The goodness of fit from these models are reported using the pseudo-R^2 statistic defined in equation 2:

$$pseudo\text{-}R^2 = 1 - \frac{Model\ deviance}{Null\ model\ deviance} \quad (2)$$

The guidance on what is a suitable geographical area on which to assume clustering takes place is to have sufficient numbers of these areas but use bigger and more aggregate clusters when possible. Potential areas are the local government district (LGD); Middle Layer Super Output Area (MSOA); Lower Layer Super Output Area; or Output Area. Table 2 provides summary statistics on the number of properties within each geography. Within OAs and LSOAs there are likely to be too few observations on which to confidently estimate the within area correlations and LGDs have the potential to be too heterogeneous and few in number. Here the properties are clustered on the compromise geography of MSOA, which has the advantage that they can be homogeneous, numerous, and contain a substantial number of properties.

Table 2 : Summary of number of rental properties in each geography

6 Model Results and Interpretation

Table 9 provides the estimates from our model, with the final column translating the parameter estimate into a percentage association with rental prices.

Table 3 : Model results

The pseudo R^2 for this model is high at 82.8%. The Generalised VIF statistic was calculated to identify any potentially multicollinearity in the model (Fox and Monette, 1992). The $GVIF^{(2/2df)}$ values are shown in the final column of Table 4

Table 4 : Grouped Variance Inflation Factors for variables used in the model

Whilst care is required when applying threshold rules of thumb for VIF statistics (O'brien, 2007), all variables but one only show moderate multicollinearity, having $GVIF^{(2/2df)}$ values below 5. The access to health services index within the AHAH domain is the only variable in the 5 to 10 range, but is retained to complete the suite of the three AHAH indices. No variables have a $GVIF^{(2/2df)}$ greater than 10.

Dealing with the non-retails aspects of the model first, as expected, the further from London, the lower the rental price. This effect is apparent in aggregated data from the Office for National Statistics (Office for National Statistics (2020) section 3) which shows inner London having the higher rents and the English Midlands having moderate rents, whilst the North East, Yorkshire and Humber and North West have amongst the lowest, with the relationship being logarithmic. As the affluence of the postcode diminishes so does the rent, with those who invest in expensive properties in more affluent areas looking for a higher rental return. For the socio-demographic categories, in vibrant cosmopolitan and ethnic areas the associated rental price is higher than in rural areas, but for more challenged socio-demographic areas such as the hard-pressed living areas it is lower. As the household income of the area increases then so does the price, identifying those renters who are able to afford the high asking rents. The desirable and rarer detached properties and bungalows all have an association with a higher price than flats. As the size of the property increases so does the price, and this is particularly marked with the number of bedrooms, whith again these results agreeing with the findings in Office for National Statistics (2020) section 1 that larger (more than 3 bedroom) properties command a significant rental price premium. For the healthiness of the neighbourhood, all the estimates are positive, meaning that a healthy environment, in trems of the quality of local retail opportunities, access to health services, green space and having good quality air are associated with a higher price. Being further from large employment centres and a railway or underground station decreases the price, meaning the renters value easy access to jobs and opportunities to travel. Relative to a major conurbation, as the area becomes more rural the impact on rental price diminishes, until there is a positive premium for scarcer properties in hamlets. Finally, as the ratings for the local school reduces, so does the price, suggesting that renters are long term, looking to locate in neighbours that can provide a good education for their children. All these associations are re-assuring in that their direction and to some extent magnitude all accord with a prior expectation as to how they might be associated with rental prices.

Returning now to the focus of this study, which is the contribution of the retail provision, we find that having a convenience grocery store close by is always associated with an increase in the rent, but this increase varies by retailer. A Waitrose effect is evident here with it being associated with the largest increase in rent (+5.8%), followed by an M&S, then Tesco, Sainsbury's and finally the Co-operative. However, the high estimate for Waitrose is not significant, possibly due to the small number of properties with a small Waitrose close by, and the lower estimates for both Sainsbury's and the Co-operative are not significant, which is a surprising result since there is an expectation any provision ("take it or leave it") would be strongly valued over no provision. Examining the impact of the brand of the closest medium to large retailer, all the other brands have a premium over an Aldi. The largest premium is again associated with a Waitrose, followed by M&S, Tesco, Sainsbury's, the Co-operative and Lidl, Aldi's fellow discounter. The rankings here largely support the interpretation of the affinities' reported in Table 1, with the possible exception of the positions of Tesco and Sainsbury's, with Sainsbury's here being generally associated with higher rental prices. Comparison estimates are not readily available, but some articles in section 4.2 estimate a retail impact on house prices to be generally a single digit percentage increase, the estimates we report here are of the same scale.

To further understand the association between retail provision and rental price Table 5 quantifies the pseudo R^2 for each factor independently, then from a grouping of individual factors into natural groups. Finally, a series of models are estimated where additional factor groupings are introduced incrementally. This sequence of models starts with just the retail provision, with here an assumption that the variation in rental prices is all associated with the retail provision. The next steps introduce the other factor groups in order of decreasing Pseudo R^2.

Table 5 : Goodness of fit statistics for single item, group and incremental models

The factors that reduce the deviance the most are associated with the distance of the property from London, recognising that London is viewed as a "property hot-spot" within England (Wilcox et al., 2017). The factor that has least influence is the quality of the local primary school, with such provision being more relevant to families with small children and less important to potential those renters who are students or young professionals. Incrementally each additional grouping increases the pseudo R^2, but the increases diminish, as the later groups struggle to account for what model deviance remains.

To illustrate how the retail impact changes as additional factors are introduced into the model, equation 1 is re-estimated several times, with Table 6 showing how the percentage impact on rental price changes as additional groups are included in the specification.

Table 6 : Percentage impact associated with retail from a series of incremental models: top, closest small store within 500m, and bottom, closest medium to large store.

With just the retail provision, having a Waitrose as the closest small retailer is associated with a near doubling of the rental listing relative to no store. More modest associations (of a near 50% increase) are associated with an M&S and a Sainsbury's. A nearby Co-operative store has little association. With medium to large stores, a similar pattern emerges; Waitrose has a near doubling relative to an Aldi, and a 50% increase for an M&S, Sainsbury's and Tesco. For the other retailers the increases are more modest, but still large. When the distance from the London is introduced these retail impacts change markedly. For both small and medium to large stores the increases become much more modest, although the Waitrose association is still large. Having a small co-operative store close by is seen to have a negative impact at this stage, although the estimate is not significant at the 95% level. After the London term, the additional factors continue to moderate the retail associations, but after Property attributes, the associations and the rankings with the retail provision remain stable leaving us with estimates that are most reliably associated with the retail provision.

7 Discussion

In this study an association between two types of retail provision and the listing rental price of residential properties have been identified and quantified. It extends the current literature by using rental prices rather than house sales and differentiates by retail brand rather than just considering accessibility to grocery stores. Use has been made of a novel data source on property rentals in England, coupled with open source data on retailer brands and their location. Other attributes have also been used to distil out the retail association.

For small convenience retail provision, having a store close by is always associated with higher rental prices, although not always significantly. The two luxury retail brands (Waitrose and M&S) have the greatest association, and the two of the Big Four retail brands that are active in this segment of the retail market (Tesco and Sainsbury's) have a modest association, whilst the Co-operative brand has only a small association. In the more competitive medium to large retail market, all brands have a greater association with higher rents than Aldi, although insignificantly for Morrison's and ASDA. The two luxury retailers have the highest association. Lidl has a greater association with rental prices than Aldi, despite them being similar Discounter retailers. The associations reported here are similar to some of the mid-single digit percentage impacts reported in section **Error! Reference source not found.**.

To ensure that the estimates from the final model do capture the true impact of the retail provision, a number of other factors are included in the model (some factors were also explored but seen to be of little value and are not reported here e.g. crime, month of sale). The direction, and to a greater extent, the magnitude associated with these other factors provides re-assurance that the housing rental market, as captured in these data, accords with previous studies. Inspecting Table 6 , with no other factors, the retail provision has a large association with the rental market, but as other factors are introduced and account for other dynamics in the local rental market, the retail association diminishes. This justifies the use of hedonic modelling over the more descriptive approach of examining the impact of just retail on house sales prices, as used by Lloyds Bank (2017) for example. The hedonic model presented in Table 3 can be used as a tool to infer a reasonable listing rent for a property, taking into account local retail provision, even in the presence of incomplete or generic property data. The model could be used in this context to identify "exorbitant" rents, i.e. those whose listing price is in excess of that predicted by the model and may also inform the tailoring of second-generation rent controls, and regulation in the housing market (Lind, 2001).

The relative popularity of each retailer exists in a state of flux (Thompson et al., 2012) with many brands periodically adapting their strategy to compete in the market (Brand-Cap, 2016). For example, the market share of the discount retail sector has grown substantially between 2015 and 2018 (Kantar Worldpanel, 2016, Steenkamp, 2018). These changes may have a knock-on effect in their association with rental prices as they become more (or less) desirable.

Whilst most homeowners would welcome the establishment of a luxury retail brand in their neighbourhood, suggesting a trend toward gentrification (Paccoud, 2017), there are potential negative social impacts associated with this for renters. The younger generation is increasingly finding the housing market a challenge, particularly if they wish to leave the rental market and become home owners (Clapham et al., 2014, Kemp, 2015, Lund, 2013, Stephens and Whitehead, 2013) and any house price premium only worsen this situation. Studies also show that those who are younger and living in greater poverty are most likely to be living in the private rented sector (Bailey, 2020). For this captive renters market, and with an increase in the use of insecure tenancies (Clarke et al., 2017), landlords have opportunities to exploit any changes in how desirable a property may be, with landlords evicting existing tenants to realise a higher rent (Alder, 2014).

Since these data are available at the unit of individual properties, it is possible to conduct separate modelling exercises based on submarkets of particular interest, either geographically or by property type, always been mindful of the impact of losing diversity in the data or modelling un-representative clusters. Further to this submarket analysis, as part of the second filtering exercise to make the commercial rental data fit for this study, those listings that were most likely to be on a per room rather than a per property basis are identified and removed from the study. However, it may be insightful to retain these data and perform a separate analysis. Such properties are likely to be attractive for a distinct submarket of renters, namely students (Rugg et al., 2002) and young professionals (Heath and Kenyon, 2001), who may have different aspirations to those of more "family" orientated renters.

Because this an observational study rather than an experiment, our findings quantify an association between retail brands and rental prices and not causation (Altman and Krzywinski, 2015). If causation is desired, then alternative techniques such as the identification of instrumental variables and a 2-stage least squares estimation (Bowden and Turkington, 1990) or a pseudo-experiment using matching, via propensity scores, (Rosenbaum and Rubin, 1983) would be required. When more recent years of data become available, the efficacy of these techniques will be investigated.

Whilst this study has been focused on the English retail market in 2015, given the continued availability of both rental data and store location data, this study could be further enhanced to track dynamics in the association between rental prices and the retail provision. Also the ubiquity of property listing sites in other countries e.g. Zillow (Zillow, 2018); RealEstate.com (Realestate.com.au, 2018) and Funda (Funda, 2018) and the availability of information on store location and branding, means that international comparative studies are possible. In terms of the other factors to include in any model, these may, however, need to be tailored to the regional market.

Reference List

ADAIR, A., MCGREAL, S., SMYTH, A., COOPER, J. & RYLEY, T. 2000. House prices and accessibility: The testing of relationships within the Belfast urban area. *Housing studies,* 15**,** 699-716.

AHMED, S., RAHMAN, M. M. & ISLAM, S. 2014. House rent estimation in Dhaka city by multi layer perceptions neural network. *International Journal of u-and e-Service, Science and Technology,* 7**,** 287-300.

ALDER, D. 2014. *The other Waitrose effect: how gentrification is linked to rising evictions* [Online]. Available: https://www.citymetric.com/business/other-waitrose-effect-how-gentrification-linked-rising-evictions-3257 [Accessed].

ALIYU, A. A., KASIM, R. & MARTIN, D. Effect of Kasuwan Laushi Super Market on Surrounding Residential Accommodations in Bauchi Metropolis, Nigeria. Proceedings of International Conference on Environment and Industrial Innovation (ICEII 2011), 2011.

ALTMAN, N. & KRZYWINSKI, M. 2015. Points of Significance: Association, correlation and causation. *Nature Methods,* 12.

BAILEY, N. 2020. Poverty and the re-growth of private renting in the UK, 1994-2018. *PLoS One,* 15**,** e0228273.

BANGURA, M. & LEE, C. L. 2020. House price diffusion of housing submarkets in Greater Sydney. *Housing Studies,* 35**,** 1110-1141.

BARON, M. G. & KAPLAN, S. 2010. The impact of 'studentification' on the rental housing market. *50th Congress of the European Regional Science Association: "Sustainable Regional Growth and Development in the Creative Knowledge Economy".* Jönköping, Sweden.

BAXTER, J. & CLARKE, J. 2013. Farewell to the tick box inspector? Ofsted and the changing regime of school inspection in England. *Oxford Review of Education,* 39**,** 702-718.

BIRKIN, M., CLARKE, G. & CLARKE, M. 2017. *Retail location planning in an era of multi-channel growth*, Routledge.

BOHMAN, H. & NILSSON, D. 2016. The impact of regional commuter trains on property values: Price segments and income. *Journal of Transport Geography,* 56**,** 102-109.

BOWDEN, R. J. & TURKINGTON, D. A. 1990. *Instrumental variables*, Cambridge university press.

BRAND-CAP. 2016. *Grocery retail in the UK* [Online]. Available: brandcap.com/wp-content/uploads/2016/04/Grocery-retail-in-the-UK.pdf [Accessed].

BURRIDGE, N. 2018. *High-end supermarkets boost house prices by £40,000* [Online]. Available: https://www.zoopla.co.uk/discover/property-news/top-end-supermarkets-boost-house-prices-by-40-000/#Bqzuhi5j8YgMCTA7.97 [Accessed].

CACI. 2018. *Acorn - The smarter consumer classification* [Online]. Available: https://acorn.caci.co.uk/ [Accessed].

CAI, L. & ZHU, Y. 2015. The challenges of data quality and data quality assessment in the big data era. *Data Science Journal,* 14.

CAMERON, A. C. & MILLER, D. L. 2015. A practitioner's guide to cluster-robust inference. *Journal of Human Resources,* 50**,** 317-372.

CERRATO CACERES, B. & GEOGHEGAN, J. 2017. Effects of New Grocery Store Development on Inner-City Neighborhood Residential Prices. *Agricultural and Resource Economics Review,* 46**,** 87-102.

CHIANG, Y.-H., PENG, T.-C. & CHANG, C.-O. 2015. The nonlinear effect of convenience stores on residential property prices: A case study of Taipei, Taiwan. *Habitat International,* 46**,** 82-90.

CLAPHAM, D., MACKIE, P., ORFORD, S., THOMAS, I. & BUCKLEY, K. 2014. The Housing Pathways of Young People in the UK. *Environment and Planning A: Economy and Space,* 46**,** 2016-2031.

CLARKE, A., HAMILTON, C., JONES, M. & MUIR, K. 2017. Poverty, evictions and forced moves. York: Joseph Rowntree Foundation.

CLARKE, I., HALLSWORTH, A., JACKSON, P., DE KERVENOAEL, R., DEL AGUILA, R. P. & KIRKUP, M. 2006. Retail restructuring and consumer choice 1. Long-term local changes in consumer behaviour: Portsmouth, 1980–2002. *Environment and planning A,* 38**,** 25-46.

CONSUMER DATA RESEARCH CENTRE. 2019. *WhenFresh/Zoopla Property Rentals and Associated Migration* [Online]. Available: https://data.cdrc.ac.uk/dataset/whenfresh-zoopla-property-rentals-and-associated-migration [Accessed].

DEL GIUDICE, V., DE PAOLA, P., MANGANELLI, B. & FORTE, F. 2017. The monetary valuation of environmental externalities through the analysis of real estate prices. *Sustainability,* 9**,** 229.

DEPARTMENT FOR TRANSPORT. 2015. *Accessibility Statistics: Travel time calculation methodology* [Online]. Available:

https://assets.publishing.service.gov.uk/government/uploads/system/uploads/attachment_data/file/474271/accessibility-statistics-travel-time-calculation-methodology.pdf [Accessed].

DEPARTMENT FOR TRANSPORT. 2017. *National Public Transport Access Nodes (NaPTAN)* [Online]. Available: https://data.gov.uk/dataset/naptan [Accessed].

DES ROSIERS, F., LAGANA, A., THÉRIAULT, M. & BEAUDOIN, M. 1996. Shopping centres and house values: an empirical investigation. *Journal of Property Valuation and Investment,* 14**,** 41-62.

DUBÉ, J., LEGROS, D. & DEVAUX, N. 2018. From bus to tramway: Is there an economic impact of substituting a rapid mass transit system? An empirical investigation accounting for anticipation effect. *Transportation Research Part A: Policy and Practice,* 110**,** 73-87.

FOX, J. 2015. *Applied regression analysis and generalized linear models*, Sage Publications.

FOX, J. & MONETTE, G. 1992. Generalized Collinearity Diagnostics. *Journal of the American Statistical Association,* 87**,** 178-183.

FUNDA. 2018. *Watching the sun rays fall into the living room* [Online]. Available: https://www.funda.nl/en/huur/ [Accessed].

GALE, C. G., SINGLETON, A. D., BATES, A. G. & LONGLEY, P. A. 2016. Creating the 2011 area classification for output areas (2011 OAC). *Journal of Spatial Information Science***,** 1-27.

GEOLYTIX. 2018a. *Geolytix Better decisions where location matters* [Online]. Available: https://geolytix.co.uk/ [Accessed].

GEOLYTIX. 2018b. *Retail Points User Guide* [Online]. Available: https://drive.google.com/file/d/0B1GCK8cPXzg-ZUl6MDFUUkFBVEU/edit [Accessed].

GIBBONS, S. & MACHIN, S. 2005. Valuing rail access using transport innovations. *Journal of urban Economics,* 57**,** 148-169.

GLAESER, E. L., KOLKO, J. & SAIZ, A. 2001. Consumer city. *Journal of economic geography,* 1**,** 27-50.

GREEN, M. A., DARAS, K., DAVIES, A., BARR, B. & SINGLETON, A. 2018. Developing an openly accessible multi-dimensional small area index of 'Access to Healthy Assets and Hazards' for Great Britain, 2016. *Health Place,* 54**,** 11-19.

HEATH, S. & KENYON, L. 2001. Single young professionals and shared household living. *Journal of Youth Studies,* 4**,** 83-100.

HENG, L., LI, V. & SKITMORE, M. 1997. Comparative study of analytical rental model and statistical models for predicting house rental levels. *Building and environment,* 32**,** 389-395.

HOOD, N., CLARKE, G. & CLARKE, M. 2015. Segmenting the growing UK convenience store market for retail location planning. *The International Review of Retail, Distribution and Consumer Research,* 26**,** 113-136.

HOSHINO, T. & KURIYAMA, K. 2009. Measuring the Benefits of Neighbourhood Park Amenities: Application and Comparison of Spatial Hedonic Approaches. *Environmental and Resource Economics,* 45**,** 429-444.

JANG, M. & KANG, C.-D. 2015. Retail accessibility and proximity effects on housing prices in Seoul, Korea: A retail type and housing submarket approach. *Habitat International,* 49**,** 516-528.

KAIN, J. F. & QUIGLEY, J. M. 1970. Evaluating the quality of the residential environment. *Environment and Planning A,* 2**,** 23-32.

KANG, C.-D. 2018. Valuing spatial access to types of retail and effects on the housing price in Seoul, Korea. *Journal of Urban Planning and Development,* 144**,** 05018007.

KANTAR WORLDPANEL. 2016. *Sales slump across major UK retailers as cheaper groceries benefit consumers* [Online]. Available: https://www.producebusinessuk.com/insight/insight-stories/2016/05/04/sales-slump-across-major-uk-retailers-as-cheaper-groceries-benefit-consumers [Accessed].

KEMP, P. A. 2015. Private Renting After the Global Financial Crisis. *Housing Studies,* 30**,** 601-620.

LAW, S. 2017. Defining Street-based Local Area and measuring its effect on house price using a hedonic price approach: The case study of Metropolitan London. *Cities,* 60**,** 166-179.

LIND, H. 2001. Rent regulation: A conceptual and comparative analysis. *European Journal of Housing Policy,* 1**,** 41-57.

LLOYDS BANK 2017. Homes close to a national supermarket ring up a price premium of £22,000.

LÖCHL, M. 2010. *Application of spatial analysis methods for understanding geographic variation of prices, demand and market success.* ETH Zurich.

LUND, B. 2013. A 'Property-Owning Democracy'or 'Generation Rent'? *The Political Quarterly,* 84**,** 53-60.

MCCLUSKEY, W., MCCORD, M., DAVIS, P., HARAN, M. & MCILHATTON, D. 2013. Prediction accuracy in mass appraisal: a comparison of modern approaches. *Journal of Property Research,* 30**,** 239-265.

MCCORD, M., DAVIS, P., HARAN, M., MCILHATTON, D. & MCCORD, J. 2014. Understanding rental prices in the UK: a comparative application of spatial modelling approaches. *International Journal of Housing Markets and Analysis,* 7**,** 98-128.

O'REILLY, L. 2015. *These Charts Show Just How Badly German Retailers Aldi and Lidl Are Hurting British Supermarkets* [Online]. Available: https://www.businessinsider.com/kantar-christmas-2015-supermarket-share-data-2015-1?r=UK&IR=T [Accessed].

O'BRIEN, R. M. 2007. A Caution Regarding Rules of Thumb for Variance Inflation Factors. *Quality & Quantity,* 41**,** 673-690.

ODUWOLE, H. & EZE, H. 2013. A hedonic pricing model on factors that influence residential apartment rent in Abuja satellite towns. *Mathematical Theory and Modeling,* 3**,** 65-73.

OFFICE FOR NATIONAL STATISTICS. 2013. *2011 rural/urban classification* [Online]. Available: https://www.ons.gov.uk/methodology/geography/geographicalproducts/ruralurbanclassifications/2011ruralurbanclassification [Accessed].

OFFICE FOR NATIONAL STATISTICS. 2018. *Research Outputs: Income from Pay As You Earn (PAYE) and benefits for tax year ending 2016* [Online]. Available: https://www.ons.gov.uk/census/censustransformationprogramme/administrativedatacensusproject/administrativedatacensusresearchoutputs/populationcharacteristics/researchoutputsincomefrompayasyouearnpayeandbenefitsfortaxyearending2016 [Accessed].

OFFICE FOR NATIONAL STATISTICS. 2020. *Private rental market summary statistics in England: April 2019 to March 2020* [Online]. Available: https://www.ons.gov.uk/peoplepopulationandcommunity/housing/bulletins/privaterentalmarketsummarystatisticsinengland/april2019tomarch2020 [Accessed].

ORFORD, S. 2002. Valuing locational externalities: a GIS and multilevel modelling approach. *Environment and Planning B: Planning and Design,* 29**,** 105-127.

ORFORD, S. 2017. *Valuing the built environment: GIS and house price analysis*, Routledge.

PACCOUD, A. 2017. Buy-to-let gentrification: Extending social change through tenure shifts. *Environment and Planning A,* 49**,** 839-856.

PECHEY, R. & MONSIVAIS, P. 2015. Supermarket Choice, Shopping Behavior, Socioeconomic Status, and Food Purchases. *Am J Prev Med,* 49**,** 868-77.

POPE, D. G. & POPE, J. C. 2015. When Walmart comes to town: Always low housing prices? Always? *Journal of Urban Economics,* 87**,** 1-13.

R CORE TEAM 2016. R: A language and environment for statistical computing.: R Foundation for Statistical Computing, Vienna, Austria.

REALESTATE.COM.AU. 2018. *Rental Properties, Homes and Aparments for rent* [Online]. Available: https://www.realestate.com.au/rent [Accessed].

ROBITZSCH, A. & GRUND, S. 2020. miceadds: Some Additional Multiple Imputation Functions, Especially for 'mice'. R package version 3.9-14.

ROSEN, S. 1974. Hedonic Prices and Implicit Markets: Product Differentiation in Pure Competition. *Journal of Political Economy,* 82**,** 34-55.

ROSENBAUM, P. R. & RUBIN, D. B. 1983. The central role of the propensity score in observational studies for causal effects. *Biometrika,* 70**,** 41-55.

RUGG, J., RHODES, D. & JONES, A. 2002. Studying a niche market: UK students and the private rented sector. *Housing studies,* 17**,** 289-303.

SCRUCCA, L., FOP, M., MURPHY, T. B. & RAFTERY, A. E. 2016. mclust 5: Clustering, Classification and Density Estimation Using Gaussian Finite Mixture Models. *R Journal,* 8**,** 289-317.

SHAW, V. 2017. 'Waitrose effect' can 'boost house prices by thousands of pounds' *The Independent*.

SIRPAL, R. 1994. Empirical modeling of the relative impacts of various sizes of shopping centers on the values of surrounding residential properties. *Journal of Real Estate Research,* 9**,** 487-505.

SONG, Y. & SOHN, J. 2007. Valuing spatial accessibility to retailing: A case study of the single family housing market in Hillsboro, Oregon. *Journal of Retailing and Consumer Services,* 14**,** 279-288.

STADELMANN, D. 2010. Which factors capitalize into house prices? A Bayesian averaging approach. *Journal of Housing Economics,* 19**,** 180-204.

STEENKAMP, J.-B. E. 2018. Brands and retailers under attack from hard discounters. *Handbook of Research on Retailing.* Edward Elgar Publishing.

STEPHENS, M. & WHITEHEAD, C. 2013. Rental housing policy in England: post crisis adjustment or long term trend? *Journal of Housing and the Built Environment,* 29**,** 201-220.

THOMPSON, C., CLARKE, G., CLARKE, M. & STILLWELL, J. 2012. Modelling the future opportunities for deep discount food retailing in the UK. *The International Review of Retail, Distribution and Consumer Research,* 22**,** 143-170.

VICKERS, D. & REES, P. 2007. Creating the UK National Statistics 2001 output area classification. *Journal of the Royal Statistical Society: Series A (Statistics in Society),* 170**,** 379-403.

WADDELL, P., BERRY, B. J. & HOCH, I. 1993. Housing price gradients: The intersection of space and built form. *Geographical Analysis,* 25**,** 5-19.

WALKER, B. & MARSH, A. 2003. Setting the rents of social housing: the impact and implications of rent restructuring in England. *Urban Studies,* 40**,** 2023-2047.

WALKER, R. E., KEANE, C. R. & BURKE, J. G. 2010. Disparities and access to healthy food in the United States: A review of food deserts literature. *Health Place,* 16**,** 876-84.

WHENFRESH. 2018. *WhenFresh provides data-driven solutions for right-time marketing* [Online]. Available: https://www.whenfresh.com/ [Accessed].

WILCOX, S., PERRY, J., STEPHENS, M. & WILLIAMS, P. 2017. United Kingdon Housing Review 2017 Briefing Paper. *Housing Review Briefing Papers.* Chartered Institute of Housing.

WILKINSON, R. & ARCHER, C. A. 1973. Measuring the determinants of relative house prices. *Environment and Planning A,* 5**,** 357-367.

WILSON, W. 2019. Rent setting: social housing (England). *London: House of Commons Library*.

XIAO, Y., ORFORD, S. & WEBSTER, C. J. 2016. Urban configuration, accessibility, and property prices: A case study of Cardiff, Wales. *Environment and Planning B: Planning and Design,* 43**,** 108-129.

ZENTES, J., MORSCHETT, D. & SCHRAMM-KLEIN, H. 2017. Strategic retail management. Springer.

ZHENG, S., XU, Y., ZHANG, X. & WANG, R. 2016. Transit development, consumer amenities and home values: Evidence from Beijing's subway neighborhoods. *Journal of Housing Economics,* 33**,** 22-33.

ZILLOW. 2018. *Find your way home* [Online]. Available: https://www.zillow.com/ [Accessed].

ZOOPLA. 2018. *Search Propoerty to Buy, Rent, House Price, Estate Agents* [Online]. Available: https://www.zoopla.co.uk/ [Accessed].

ZUUR, A. F., IENO, E. N., WALKER, N. J., SAVELIEV, A. A. & SMITH, G. M. 2009. GLM and GAM for count data. *Mixed effects models and extensions in ecology with R.* Springer.

Table 7 : Customer base by retailer. Adapted from Thompson et al. (2012)

Retailer(s)	Type of retailer	Overrepresentation
Waitrose	Luxury	Affluent city living
Marks and Spencer (M&S)	Luxury	Prospering suburbs
Sainsbury's	Higher end mass market	Prospering suburbs
Tesco	Mass market	Prospering suburbs
The Co-operative Group	Co-operative	Countryside
Morrison's	Lower end mass market	Blue collar
ASDA	Lower end mass market	Constrained by circumstances
Aldi	Discounter	Constrained by circumstances
Lidl	Discounter	Blue collar

Table 8 : Summary of number of rental properties in each geography

Geography	Count	Minimum	Lower quartile	Mean	Median	Upper quartile	Max
LGD	325	191	961	2288.7	1528	2764	13925
MSOA	6788	4	49	109.6	78	130	1236
LSOA	32693	1	8	22.8	15	28	491
OA	139820	1	2	5.3	3	7	409

Table 9 : Model results

Variable	N or average	Estimate	Std. Error	t value	Pr(>|t|)	Impact
Intercept	743817	5.3768	0.0400	134.34	0.0000	
None within 500m	488824					0.0%
Co-operative	66611	0.0076	0.0097	0.79	0.4320	0.8%
Sainsbury's	60872	0.0115	0.0102	1.13	0.2574	1.2%
Tesco	115073	0.0261	0.0071	3.68	0.0002	2.6%
M&S	10823	0.0506	0.0179	2.83	0.0047	5.2%
Waitrose	1614	0.0562	0.0513	1.09	0.2736	5.8%
Aldi nearest medium/large store	66834					0.0%
Asda	73768	0.0016	0.0082	0.19	0.8492	0.2%
Morrison's	66855	0.0034	0.0111	0.31	0.7590	0.3%
Lidl	76555	0.0266	0.0081	3.29	0.0010	2.7%
Co-operative	104760	0.0363	0.0085	4.26	0.0000	3.7%
Sainsbury's	102817	0.0574	0.0087	6.60	0.0000	5.9%
Tesco	112346	0.0618	0.0093	6.61	0.0000	6.4%
M&S	67319	0.0866	0.0112	7.70	0.0000	9.1%
Waitrose	72563	0.1110	0.0111	10.00	0.0000	11.7%
Distance East/West London (log)	76.6km	-0.0766	0.0036	-21.33	0.0000	0.7%[1]
Distance North/South London (log)	105.0km	-0.1069	0.0036	-30.07	0.0000	1.0%[1]
Affluent Achievers	95272					0.0%
Rising Prosperity	210185	-0.2041	0.0168	-12.13	0.0000	-18.5%
Comfortable Communities	152719	-0.1873	0.0108	-17.32	0.0000	-17.1%
Financially Stretched	135891	-0.2158	0.0146	-14.81	0.0000	-19.4%
Urban Adversity	145080	-0.2758	0.0146	-18.87	0.0000	-24.1%
Not in Private Household	4466	-0.1512	0.0180	-8.39	0.0000	-14.0%
Acorn Unknown	204	0.0584	0.0718	0.81	0.4158	6.0%
Rural Residents	37986					0.0%
Cosmopolitans	140398	0.1903	0.0125	15.27	0.0000	21.0%
Ethnicity Central	78305	0.1907	0.0123	15.49	0.0000	21.0%
Multicultural Metropolitan	124128	0.0360	0.0096	3.73	0.0002	3.7%
Urbanites	180969	0.0532	0.0069	7.71	0.0000	5.5%
Suburbanites	65823	-0.0118	0.0068	-1.73	0.0836	-1.2%
Constrained City Dwellers	43308	0.0311	0.0093	3.33	0.0009	3.2%
Hard-Pressed Living	72900	-0.0162	0.0081	-2.00	0.0450	-1.6%
Household Income	£22,764	0.000014	0.000001	16.40	0.000000	1.4%[2]
Flat property type	324550					0.0%
Bungalow	18322	0.0765	0.0051	14.87	0.0000	8.0%
Detached	51223	0.0496	0.0067	7.41	0.0000	5.1%
Semi-detached	81946	-0.0085	0.0053	-1.61	0.1073	-0.8%
Terraced	166321	0.0072	0.0044	1.63	0.1038	0.7%
Unknown Type	101455	0.0421	0.0046	9.10	0.0000	4.3%
One bedroom	143327					0.0%
Two bedrooms	295421	0.2641	0.0027	97.03	0.0000	30.2%
Three Bedrooms	188705	0.5021	0.0056	89.00	0.0000	65.2%
Four bedrooms	64375	0.7684	0.0061	125.04	0.0000	115.6%
Five bedrooms	18619	1.0311	0.0081	127.62	0.0000	180.4%
Six or more bedrooms	9825	1.3254	0.0133	99.61	0.0000	276.4%
Unknown Bedrooms	23545	-0.1435	0.0111	-12.96	0.0000	-13.4%
One bathroom	260159					0.0%
Two bathrooms	59053	0.0861	0.0035	24.74	0.0000	9.0%
Three bathrooms	8633	0.2031	0.0130	15.64	0.0000	22.5%
Four or more bathrooms	2028	0.3398	0.0190	17.84	0.0000	40.5%

Unknown bathrooms	413944	0.0579	0.0033	17.60	0.0000	6.0%
One reception	211569					0.0%
Two receptions	56564	-0.0038	0.0033	-1.13	0.2598	-0.4%
Three receptions	6652	0.0502	0.0080	6.31	0.0000	5.1%
Four or more receptions	1237	0.2088	0.0228	9.17	0.0000	23.2%
Unknown receptions	467795	-0.0193	0.0032	-6.11	0.0000	-1.9%
Retail Health	33.74	0.00148	0.00018	8.03	0.00000	1.5%[3]
Health Services	13.61	0.00043	0.00025	1.73	0.08378	0.4%[3]
Environment Health	31.72	0.00030	0.00021	1.45	0.14716	0.3%[3]
Distance to large employment centre (log)	4.56km	-0.0247	0.0038	-6.45	0.0000	0.2%[1]
Distance to nearest railway/Underground station (log)	2.09km	-0.0144	0.0031	-4.58	0.0000	0.1%[1]
Major Urban Conurbation	314495					0.0%
Minor Urban Conurbation	24752	-0.1373	0.0155	-8.87	0.0000	-12.8%
Urban City and Town	329262	-0.0731	0.0071	-10.33	0.0000	-7.1%
Rural Town	45663	-0.0715	0.0093	-7.68	0.0000	-6.9%
Village	19540	-0.0381	0.0118	-3.22	0.0013	-3.7%
Hamlet	10105	0.0524	0.0129	4.07	0.0000	5.4%
Outstanding Primary	140090					0.0%
Good Primary	470710	-0.0133	0.0061	-2.19	0.0283	-1.3%
Requires Improvement Primary	121732	-0.0199	0.0085	-2.34	0.0192	-2.0%
Inadequate Primary	11285	-0.0336	0.0107	-3.14	0.0017	-3.3%
Outstanding Secondary	177902					0.0%
Good Secondary	376432	-0.0136	0.0079	-1.72	0.0861	-1.4%
Requires Improvement Secondary	148590	-0.0453	0.0108	-4.21	0.0000	-4.4%
Inadequate Secondary	40893	-0.0493	0.0104	-4.74	0.0000	-4.8%

[1] For a 10% increase in distance $1 - (1 + 0.1)^{\beta}$

[2] For a £1,000 increase in income $(e^{1000\beta} - 1)$

[3] For a 10 point increase in score $(e^{10\beta} - 1)$

Table 10 : Generalised Variance Inflation Factors for variables used in the model

	Degrees of freedom (df)	GVIF	$GVIF^{(1/2df)}$	$GVIF^{(2/2df)}$
Closest small retailer within 500m	5	8.5	1.24	1.53
Closest medium to large retailer	8	7.2	1.13	1.28
Distance east/west of London (km)	1	4.7	2.17	4.72
Distance north/south of London (km)	1	5.0	2.23	4.99
ACORN Category	6	70.2	1.43	2.03
OAC super group	7	137.1	1.42	2.02
Household Income	1	4.7	2.16	4.66
Property Type	5	20.5	1.35	1.83
Number of Bedrooms	6	27.0	1.32	1.73
Number of Bathrooms	4	21.7	1.47	2.16
Number of Reception rooms	4	7.4	1.28	1.65
Retail healthiness	1	4.2	2.05	4.21
Heath services	1	6.5	2.56	6.54
Environmental healthiness	1	3.3	1.81	3.26
Distance to large employment centre	1	3.2	1.78	3.18
Distance to railway/underground station	1	2.9	1.71	2.91
Rural/Urban classification	5	12.9	1.29	1.67
OFSTED rating of primary school	3	1.8	1.11	1.23
OFSTED rating of secondary school	3	3.5	1.23	1.51

Table 11 : Goodness of fit statistics for single item, group and incremental models

Factors	Pseudo R^2 (%)	Group Pseudo R^2 (%)	Incremental Pseudo R^2 (%)
Closest small retailer within 500m	7.9		
Closest medium to large retailer	11.1	16.7	16.7
Distance east/west of London (km) (logged)	35.2		
Distance north/south of London (km) (logged)	39.4	46.3	49.9
ACORN Category	21.0		
OAC super group	21.0	35.7	56.3
Household Income	34.8	34.8	57.3
Property type	3.1		
Number of bedrooms	20.9		
Number of bathrooms	11.1		
Number of reception rooms	2.3	32.7	82.0
Retail healthiness	8.5		
Health services	4.3		
Environmental healthiness	15.1	16.4	82.3
Distance to closest large employment centre (km) (logged)	6.7		
Distance to the nearest railway/underground station (km) (logged)	13.0	14.9	82.5
Rural/Urban classification	14.8	14.8	82.7
OFSTED rating of nearest primary school	2.6		
OFSTED rating of nearest secondary school	6.6	8.6	82.8

Table 12 : Percentage impact associated with retail from a series of incremental models: top, closest small store within 500m, and bottom, closest medium to large store.

Retailer	Retail	+London	+Classification	+Income	+Property	+Healthiness	+Access	+Urban Rural	+Education
Small Store (reference : None)									
Waitrose	**91.3%**	**25.2%**	**13.6%**	*9.6%*	*7.9%*	*6.7%*	*6.9%*	*6.7%*	*5.8%*
M&S	**51.4%**	**8.8%**	**7.4%**	**6.7%**	**8.6%**	**6.4%**	**5.1%**	**5.5%**	**5.2%**
Tesco	**30.7%**	**3.5%**	**4.1%**	**3.9%**	**5.5%**	**2.7%**	**2.5%**	**2.7%**	**2.6%**
Sainsbury's	**49.3%**	**8.1%**	**6.5%**	**6.6%**	**5.0%**	*1.4%*	*1.0%*	*1.4%*	*1.2%*
Co-operative	*2.3%*	-2.4%	*0.2%*	*0.7%*	1.9%	*0.1%*	*0.2%*	*0.8%*	*0.8%*
Medium to Large Store (reference : Aldi)									
Waitrose	**96.5%**	**30.2%**	**16.5%**	**12.3%**	**11.7%**	**11.8%**	**11.7%**	**11.8%**	**11.7%**
M&S	**54.1%**	**16.3%**	**8.6%**	**6.6%**	**9.0%**	**9.1%**	**8.3%**	**8.8%**	**9.1%**
Tesco	**47.9%**	**11.4%**	**5.8%**	**5.0%**	**5.8%**	**6.1%**	**6.3%**	**6.3%**	**6.4%**
Sainsbury's	**51.1%**	**13.4%**	**6.8%**	**5.8%**	**5.3%**	**5.9%**	**5.8%**	**5.9%**	**5.9%**
Co-operative	**22.3%**	**8.6%**	**3.9%**	**3.5%**	**2.7%**	**3.1%**	**3.7%**	**3.7%**	**3.7%**
Lidl	**18.9%**	*2.2%*	*2.0%*	**2.1%**	**2.3%**	**2.3%**	**2.7%**	**2.7%**	**2.7%**
Morrison's	**15.8%**	*1.9%*	*-1.2%*	*-1.2%*	*-0.3%*	*0.4%*	*0.4%*	*0.3%*	*0.3%*
ASDA	**9.0%**	*0.5%*	*0.5%*	*0.4%*	*0.2%*	*0.4%*	*0.4%*	*0.0%*	*0.2%*

Note : **Bold** significant at 95%

Normal significant at 90%

Italic insignificant at 90%

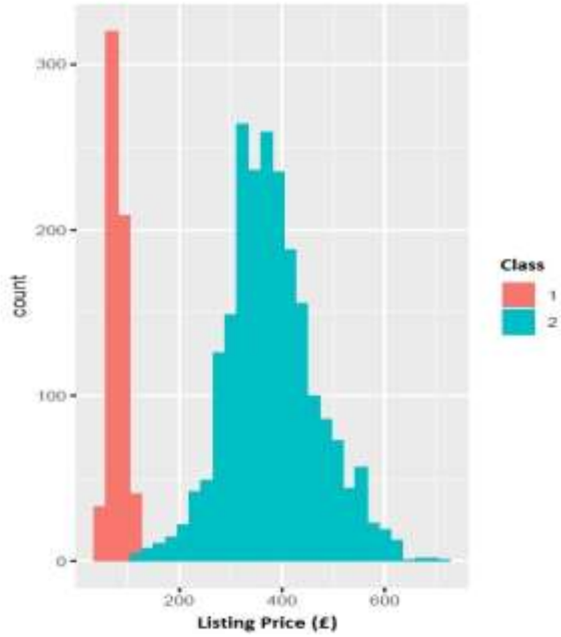

Figure 3 : Distribution of listing prices for five bedroom terraced properties

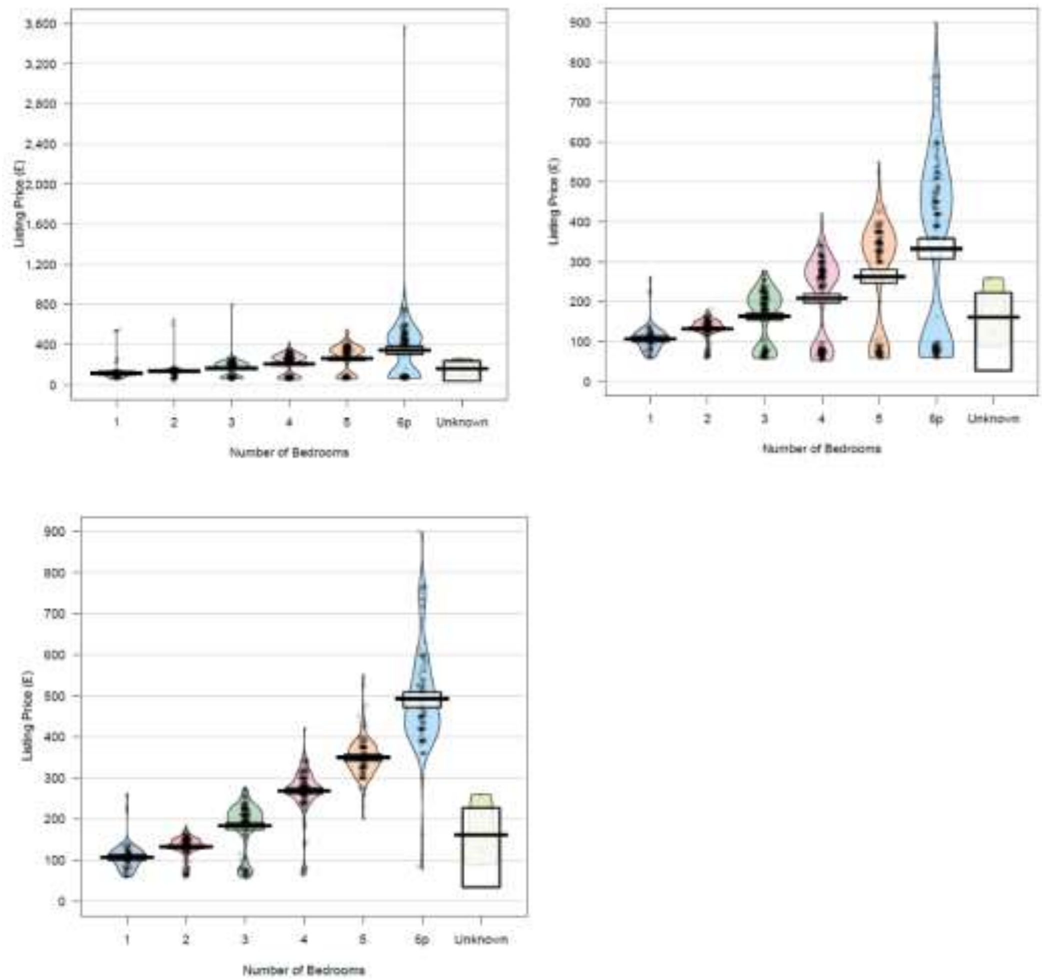

Figure 4 : Distribution of rental listing price in Hyde Park, Leeds, by the number of bedrooms (a) Original data; (b) Trimmed data; (c) Segregated data