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What Property Attributes are Important to UK University Students in their Online Accommodation Search?

Abstract

Purpose- This paper examines the categories of property attributes that are important to UK university students in their online accommodation search. It also analyses the volume of information displayed regarding the property attributes and explores the influence of some of the information provided on the attractiveness and by extension, the booking potential of the property.

Design/methodology/approach- The authors use data from an online student accommodation listing platform – student.com which contains tangible and intangible property attributes, and the data is analysed using a hedonic regression model.

Findings- The results show that Purpose-built Student Accommodation's (PBSA) tangible and intangible attributes are important to students in their online accommodation search, although, these attributes vary in impact. The study also reveals that failure to display key information of a PBSA may reduce the attractiveness of the property.

Originality- The empirical evidence on student accommodation ex-ante preferences and choices is limited, particularly as it relates to online accommodation search in a UK context. The authors' approach to identify the application of the search theory to the student accommodation search process is particularly unique.

Keywords: Operational real estate, purpose-built student accommodation, PBSA, PropTech, online search, hedonic model

JEL Codes: R21, R30, D83, O30

1.0 Introduction

1.1 Background

The Purpose-Built Student Accommodation (PBSA) market is one of the most mature and most liquid of the operational real estate sectors in the UK. Savills Research (2019) reveals that, as of 2019, there were about 1,844,500 students in the UK and a stock of 640,000 rooms valued at £51.2bn. The report further indicates that investment capital flow to the PBSA sector from 2016 to 2018 was estimated at £4.1bn. Despite the COVID-19 pandemic-induced economic challenges and the political uncertainty associated with Brexit, UK's university student enrolment remained high in 2020 (Guardian, 2020; Staton, 2020; UCAS, 2020); thus, the market has maintained a positive outlook.

Notwithstanding the rapid growth and positive outlook, there is insufficient scholarly insight on the student accommodation market, particularly for PBSA assets. Literature on student accommodation is generally skewed to the investment side of the market (see French *et al.*, 2018 and Newell and Marzuki, 2018), the morphology of the accommodation (see Amole, 2009) and student satisfaction and academic performance (see Oke *et al.*, 2017; Ong *et al.*, 2013; Thomsen, 2007; Thomsen and Eikemo, 2010). These studies, however, do not offer insight on student accommodation search and selection. This paper, therefore, attempts to address this knowledge gap by providing insights on how listing or failing to list some key property information can affect the attractiveness of a property to UK university students. This can also extend the knowledge on the property attributes that are important to UK students in their online accommodation search, and by extension, the ways in which the display of some of these factors can potentially affect the demand for PBSAs.

This study investigates the following key questions:

1. What are some of the major listed property attributes that are important to

university students in their online accommodation search?

2. What category of the listed property attributes (tangible or intangible) have the most profound effects on the popularity of a PBSA[1]?
3. How does the information displayed on the attributes of a PBSA affect the level of interest that the property will generate, and by extension, the booking potential of a PBSA?

The data used in this study is sourced from Student.com – one of the major online marketplaces for student accommodation search and booking in Europe and the UK. Using a cloud-based web scraper, we implement an automated procedure for the collection and storage of the data. The dataset in our study includes information relating to the popularity score, tangible attributes, and intangible attributes of the listed PBSAs in 12 major UK cities. We adopt a hedonic modelling approach, and the results reveal that the tangible and intangible displayed attributes of a PBSA are important to UK university students in their online accommodation search. We do not observe clear differences in the magnitude of the effects of tangible or intangible property attributes. The results also suggest that students may find properties with less information less attractive and find properties with more information more attractive. These results imply that displaying more property attributes can increase the booking potential of an online listed PBSA.

This study makes an important contribution by providing empirical evidence on the link between the information displayed on a student online listing platform and the potential demand for the property. This insight is valuable, particularly considering that the PBSA is a niche market with relatively insufficient micro-level information. The insight from the study can also aid the development of more effective PBSA investment and development strategies. With increasing investment flow into the UK, investors and developers can identify specific attributes that matter the most to students and thus

[1] The popularity score of a PBSA is the number of students that have saved the property to their wishlist.

maximise the return on their investment. Portfolio managers who hold PBSA assets can also use the insight to identify the property attributes with the highest potential to add value to their assets and maximise portfolio efficiency. Furthermore, asset and property managers can develop strategies to ensure optimal asset performance and identify the property attributes that their marketing should highlight and emphasise when listing their properties online.

This paper continues with an overview of the evolution of student accommodation as an asset in the next section and a third section provides an overview of PropTech and student online accommodation search. The fourth section provides a review of relevant literature, and the fifth and sixth sections discuss the methods and results, respectively. The final section provides a summary and conclusion to the paper.

1.2 Student Accommodation as an Asset: evolution and prospects

University student accommodation in the UK was conventionally provided and managed by higher institutions. However, the inability of universities to meet the growing student accommodation demand (Newell and Marzuki, 2018) and the use of external funding for capital projects in the UK Higher Education sector (McCann *et al.*, 2019) created a market for private investment, mainly through houses in multiple occupation (HMOs) and PBSAs.

The emergence of the PBSA as an investment asset in the UK can be linked to the listing of Unite Students on the Alternative Investment Market (AIM)- a submarket of the London Stock Exchange in 1998[2]. Following this, GCP Student became the first UK student accommodation REIT listed on the London Stock Exchange, creating a path for several other student accommodation REITs, and resulting in an increase in capital flow to the sector. With the returns on student accommodation assets (9.4% in 2018) surpassing the total returns of all commercial assets in the UK, coupled with the positive market

[2] This was later transferred to the London Stock Exchange in 2000.

sentiments, the UK student accommodation market continues to attract huge domestic and international funds (CBRE Research, 2019).

International students constitute 23% of the UK's full-time university student population, representing a growth of 54% in the last decade (Cushman & Wakefield, 2019). Savills Research (2020) further reveal that the international students' growth rate is 10 times faster than the growth rate of domestic students. The continuous increase in the enrolment of international students may be associated with the high standard of the UK higher education system, increased funding in UK higher education sector and the removal of student number caps (Cushman and Wakefield, 2019). Savills Research (2020) further reveals that 60% of international students are more likely to live in PBSAs, suggesting that the continued increase in international students' enrolment can further expand the PBSA market.

1.3 PropTech and Students' Accommodation Search

PropTech[3] has spread across the value chain of real estate (Barkham *et al.*, 2018; Hughes, 2017) creating several products, applications, and online platforms (Saiz, 2020). It has specifically changed the search, selection and booking process of student accommodation, particularly PBSAs. Thus, online platforms such as Uniplaces, Universityling.com, Student.com, Uhomes, Unilodgers Roomiapp etc, have become popular among UK university students. These innovations now make marketing, search, reservation and booking of student accommodation more efficient for both operators and students. Furthermore, researchers can collect and store data from these platforms using advanced techniques such as automated web scraping, to enhance empirical analysis.

There is a paucity of empirical analysis on digital applications to real estate. Some

[3] PropTech can be described as the deployment of digital and IT applications to the different elements of the value chain of real estate typically to enhance and maximise economic, social, environmental, or physical efficiency.

strands of PropTech literature review and discuss the progress, growth, and projections of digital applications in real estate (see Barkham *et al.*, 2018; Saiz, 2020; Saull and Baum, 2020). These studies however do not employ empirical analysis. Saull *et al.* (2020) and Shaw (2018) make valuable contributions by providing insight based on empirical analysis, although, the focus is not on the users. The strand of literature that focuses on the users relates to hospitality, particularly hotels, covering areas such as online purchase behaviour (see Heijden *et al.*, 2003; Gavilan *et al.*, 2018; Senecal and Nantel, 2004; Zhao *et al.*, 2015). It will therefore be valuable to extend these areas of knowledge to student online accommodation search and booking, supporting the insight with empirical evidence.

2.0 Literature Review

This study aligns to two interconnected strands in the existing body of literature: the first is the information, search process and the selection of high involvement goods; the second is student accommodation.

2.1 Information, Search Process and Selection for High Involvement Goods

The classic consumer behaviour theory underscores the complexity of consumers' decision making and selection processes, particularly those relating to many offerings and high-priced goods associated with economic and financial commitments. The search theory further provides insight into individuals' conscious and unconscious optimal strategies when choosing from a series of potential opportunities of random quality with a combination of attributes that require trade-offs among a set of offerings. Economists initially applied the search theory to labour economics (Jovanovic, 1979; McCall, 1970) and this was further applied to macroeconomics through the matching theory (see Diamond, 1984). The main point of convergence in these studies is the role of cost and search friction associated with factors such as time, consumer circumstances and the quality and quantity of information in important decision making, particularly for high involvement goods.

The search theory has also been extended to housing economics with insight inot the search and selection of different segments of the housing market, albeit a significant proportion seems to be directed at the sales market. For instance, Albrecht *et al.* (2016), Turnbull and Sirmans (1993) and Williams (2018) focus on links between information, search, sales/purchase and house prices. Other studies (such as Blowers *et al.*, 2014; Kim, 1992; Read, 1993, 1997) have also shown that the lack of information in the rental segment of the market may be costly, particularly for potential tenants. Given the acute information asymmetry in real estate markets arising from heterogeneous and multiple players in the market, the level of information plays an important role in the search process. Qiu and Zhao (2018) particularly argue that access to a better pool of information will be beneficial to individuals in search of accommodation. This study further highlights the impact of asymmetric market information on households' housing choices and empirically examines the varied behaviour between better informed and less informed individuals in a housing market.

The advancement in information technology has reduced information asymmetry in the real estate search process (Palm and Danis, 2002), with individuals increasingly relying on information listed on a property to make their housing decision. This area of research has not been extended to student accommodation search; it will therefore be valuable to analyse the relationship between the information listed on student accommodation websites and students' accommodation preferences.

2.2 Student Accommodation Research

Real estate market reports are important sources of current data and information on the student accommodation market[4]. These reports are however descriptive, typically providing aggregated market information and usually with minimal empirical analysis. The research by French *et al.* (2018) provides useful insight into the student accommodation market, although this paper is also without empirical data analysis. Newell and Marzuki (2018) make an important contribution by providing an empirical analysis of data on investment returns. These articles and reports offer a macro-level perspective to the market, mainly focusing on investment and development markets; thus, the insight may be more suitable for a top-down investment approach. Although these insights are important for investment, there is a need for investors, developers, fund managers, asset managers and property managers to gain deeper insight into the user/occupier segment of the market and this may require a more micro-level approach.

Some scholars provide more micro-level insight on the student accommodation market, with a general focus on student satisfaction, living environment, and academic performance. These studies reveal that students are significantly affected by tangible/physical attributes[5] and intangible/abstract features[6] of their accommodation. Research has shown that the size of the wardrobe/closet, laundry services and window quality affect students' satisfaction (see Amole, 2009; Thomsen, 2007; and Oke *et al.*, 2017). Studies also show that students are more satisfied with their accommodation if they have private rooms, and if they find the physical environment, aesthetics, architectural and morphological features of the property to be pleasing, particularly if the building is newly constructed or renovated (see Amole, 2009; Thomsen, 2007). Khozaei *et al.* (2014) further reveal that students prefer single rooms to double-sharing rooms, even if they have to share bathrooms. Other studies on shared facilities (such as

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[4] Student accommodation market analysis now features prominently in the periodic market reports of leading real estate firms such as JLL, Knight Frank, Savills etc.

[5] Tangible attributes are the physical elements of the students' rooms (such as the bed size, desk, chair, etc) and their flats/houses (such as number of people in the house, number of rooms in the flat/house etc).

[6] Intangible attributes relate to non-physical elements of the property (such as rating scores, rent, reviews etc).

Khozaei *et al.*, 2011) did not find sharing of kitchen facilities statistically significant, although it was observed that students prefer properties with good security systems, room privacy and flexibility.

Intangible attributes of student accommodation have also been found to have certain effects on students. For instance, Khozaei *et al.* (2011), Magni *et al.* (2019), and Thomsen and Eikemo (2010) find that location and distance (to the commercial centre and amenities) are important to students. Kobue *et al.* (2017) and Kolawole and Boluwatife (2016) also buttress the importance of location to students, although, their findings suggest that students may be more concerned about other intangible factors such as the distance to their institutions of study perceived security, rent, and peer' opinion/recommendation. Although the effects of the distance to the institutions of study may vary by country, transportation modes and living arrangement, the studies of Kobue *et al.* (2017) and Kolawole and Boluwatife (2016) posit that the commute distance to the institution of study remains an important consideration in students' accommodation satisfaction. It would therefore be valuable to analyse these attributes in the context of the students' online accommodation search.

2.3 Summary of Research Gaps and Contributions

The review of the literature highlights the advancement of knowledge in the related themes to our study. We, however, identify some gaps in the literature and thus make contributions to these areas. First, we make a unique contribution to the literature on the student accommodation preferences ex-ante, with valuable insight into student accommodation investment, development, and management. Second, we provide insight on the role of digital technology in students' accommodation search and selection through the identification of the property attributes that are most important to students. Deeper insight is also provided on the effects of failing to list some property attributes. Third, our study covers a broader scope and a larger sample size in comparison to previous studies. Related studies are typically limited to a single university in a city and often with a small sample. For instance, Magni *et al.* (2019) uses a sample size of 338 students in a single university in an Italian city while Kobue *et al.* (2017) use a sample size of 55 students- also in one university in a South African city. Furthermore, Khozaei *et al. (*2014) have a sample of 752 students in one institution in a Malaysian city while the study of Kolawole and Boluwatife (2016) also focuses on an institution in one city in Nigeria. These sampling designs have limitations such as the limited scope of application; they therefore cannot be generalised to the whole population[7]. Fourth, much of the literature on micro-level student accommodation is skewed to Asia and Africa; our study will therefore make a valuable contribution to the UK context.

It should be noted that most of the studies reviewed were conducted in different geographical contexts and the results may therefore not be applicable to the UK and other geographical contexts outside the study area. The potential areas of variation could be differences in transportation systems, tastes, preferences, and expectations. For instance, the effect of the distance between the property and the target higher institution may be less significant in counties with more efficient transportation systems than it would be in countries with less efficient transportation systems. However, factors such as shared facilities, entertainment and bed sizes may have similar effects regardless of geographical contexts.

3.0 Data and Methods

3.1 Data

This study analyses the link between the potential demand for a student accommodation property and the property's online displayed attributes. There is therefore the need to

[7] These studies also generally follow a descriptive analytical approach, and the outcome variables are generally subjective.

identify a student accommodation web-based listing platform that displays a suitable demand indicator and the attributes of the properties. Student accommodation listing platforms typically display the attributes of the listed properties but do not display the number of bookings for the properties (which would be the ideal demand indicator). Student.com however provides an alternative indicator i.e., the popularity score for properties listed. This popularity score is in a sense, an indication of the booking potential of a listed PBSA as it captures the potential of selection to wishlist.

Student.com is an online student accommodation search and booking platform with global coverage and has been operational for more than six years. In addition to displaying the attributes of the listed properties, this platform enables students to save rooms of interest to their wishlists and request to book the room. The wishlist is a particularly important feature of this platform as it enables students to shortlist properties of interest and save them while continuing their online search. The number of students that save a property to their wishlist on Student.com is the popularity score of the property, and this is displayed as "popular" on the listing page of each property. This study adopts the popularity score as the outcome variable, and this is utilised as the demand proxy. Suffice to state that ideally, the data on the number of bookings for each property would be suitable as the outcome variable; however, this information is not displayed on the website and is unavailable through other avenues. We acknowledge that there may be some measurement error in the outcome variable because the popularity score as a demand proxy may not translate to actual demand. However, it has been established in the literature that measurement errors in dependent variables do not lead to biased estimates, they only result in less precise estimates i.e. estimates with larger standard errors (see Wooldridge, 2002).

The data from student.com was retrieved using an automated cloud-based web/data scraping procedure[8]. The data covers the listed student accommodation properties in 12

[8] The data was scraped from the platform on 17 December 2020.

major UK cities. The rationale for the city selection is two-fold: first, we select the seven UK cities ranked in the top-10 most popular student cities in the world (based on the Times Higher Education guide of 2018) ranking: London, Manchester, Glasgow, Liverpool, Nottingham, Sheffield, and Birmingham. In addition to these, we include five other UK cities which, though having the highest population in the UK, were not listed in the 2018 Times Higher Education top-10 most popular cities ranking: Bristol, Leicester, Edinburgh, Leeds, and Cardiff. The dataset contains a total of 4,195 rooms in 960 student accommodation properties (see Appendix Table I for further information). The variation observed in Appendix Table I suggest that city market indicators and performance vary across the UK- an indication of the potential city-level heterogeneity in the data, and the need to introduce controls for city-fixed effects in the empirical analysis.

To make the data compatible with the empirical exercise, we transform and recalibrate the outcome and explanatory variables. The outcome variable (popularity score) has a wide distribution of values (0-2045) and a standard deviation of 358. To minimise the effect of the high variability in this variable, a positive value of 1.5 is added uniformly to all the values of the popularity score, after which the natural logarithms of the new popularity score values are derived. This approach addresses the issues associated with zero values and heteroscedasticity, particularly with 10% of the popularity scores in the dataset having zero values (see Appendix Table II for details, description, configuration and summary statistics for the outcome and explanatory variables).

Most of the explanatory variables are either in binary or continuous variable forms and some of these variables have zero observations. The zero observations in the categorical and binary variables are however handled differently from the dependent variable. These zero observations are categorised as a valid category, as they capture the number of properties where the property attributes were not displayed at the time of collecting the data. Suffice to state that the effects of failing to display some property attributes is of particular interest to us in this study. Apart from the location (city) variable (which does not have missing observations), all the other categorical variables have a category for "no information displayed on the attribute" =0 (for $x_0, x_1, x_2....x_n$). Furthermore, we convert the "transition time to HEI 1" variable (originally continuous variable) to a categorical variable to also enable us to capture the effects of not displaying the transit time. In addition to this, the binary variables capture the effect of "displaying a property attribute" =1, relative to "no information displayed on the attribute" =0 (for x_0, x_1).

The categorisation above is mainly set to capture the effect of different measures of the variables relative to not providing information on the variable and other categories. Some explanatory variables however do not have missing information and are therefore not re-categorised. These variables are price, reviews, private bathroom, and private kitchen. The "price of the room" (rent per week) variable is a continuous variable, and it is transformed using natural logarithms. The number of reviews written on each property is also a continuous variable and although the variable has some "zero" values, these "zeros" imply that no student has written a review on the property; thus, the zero values are not classified as "missing" and due to the low variance in the variable, the linear form is maintained. The other two features (private bathroom and private kitchen) are binary variables, although, these are relative to shared bathroom and shared kitchen respectively.

3.2 Empirical Framework

This study aims to estimate the effect of the listed attributes of a PBSA property on the property's popularity score using a hedonic model approach. The attributes are characterised as tangible (such as bed size) and intangible (such as distance and price). It can therefore be inferred that the popularity score of property i in market j is a function of K number of characteristics measured by Z

$$Popularity\ score_{ij} = f(Z_{i1}, Z_{i2}, Z_{i3}, \ldots, Z_{ik}, \varepsilon_i) \ldots\ldots\ldots\ldots\ldots\ldots (1)$$

Where ε_i is the error term. The partial derivative of $Popularity\ score_{ij}(*)$ with respect to the k_{th} *PBSA feature* $\frac{\delta Popularity\ score_{ij}}{\delta Z_k}$ is referred to as the marginal implicit popularity score which represents the marginal popularity score of the k_{th} property feature in the overall popularity score of the PBSA property. To estimate the marginal contribution of each characteristic using traditional regression techniques, we need to specify equation (1) as a parametric model. We implement the log-linear functional form due to the definition of our outcome variable as stated in the data section. The log-linear function form allows each attribute of the PBSA property to be interpreted as a percentage of the marginal utilities of the accommodation which is an added advantage.

The log-linear hedonic model is specified

$$Ln(Popularity\ score_{ij}) = \alpha + X'_{ir}\beta + Z'_i\delta + n'_i\gamma + f_j + \varepsilon_i \ldots\ldots\ldots. (2)$$

Where $Ln(Popularity\ score_{ij})$ is the natural logarithm of the popularity score of PBSA property i in market j, α is the intercept term, β, δ, and γ are the slope parameters associated with different tangible and intangible characteristics of the property. X'_{ir} is a vector of room-specific tangible characteristics, Z'_i is a vector of property-specific tangible characteristics, n'_i is a vector of intangible property characteristics, f_j is city fixed effects and ε_i is the error term. The room-specific tangible characteristics include room furniture, number of beds and bed size, while the property-specific tangible characteristics include the number of rooms in the flat, bathroom use, kitchen use, laundry, access control, security, cinema room, entertainment room and television. The intangible characteristics are rating, the number of reviews, bills, rules, having a site manager on the property and the transit time.

We estimate equation (2) using the ordinary least squares (OLS) linear regression model and include city fixed effects in all the models. This is important because of variation in indicators (as shown in Table I) and because housing markets are location specific, thus, results from one location may not easily be generalised to other locations. In addition to this, the fact that some properties may have more rooms represented in the sample than others implies that the error terms are likely to be correlated within the properties, thus, the standard error is clustered at the property level in all models.

We estimate four different models using OLS for the pooled analysis. The first specification is a regression of the natural log of PBSA property score on intangible attributes of the property. Next, we estimate a model for the room-specific tangible characteristics and another model for the property-specific tangible characteristics. After this, we estimate a model on both the room-specific and property-specific tangible characteristics, and finally, we estimate a model with all the room and property-specific tangible and intangible characteristics. This is the full specification and is thus our preferred model. The results of the analysis are presented in the next section.

4.0 Results and Discussion

This section presents and discusses the results from the empirical analysis in four sub-sections: the first sub-section analyses key displayed property attributes and their effects on the popularity score of PBSAs; the second sub-section analyses the effects of displaying/not displaying key property attributes on the property's popularity score; the third sub-section focuses on the analysis of locational sub-markets, and finally, further robustness tests are reported and discussed in the fourth sub-section.

4.1 The Effects of Displayed Property Attributes on the Popularity Scores of PBSAs

The OLS regression estimations in this sub-section show the effects of the tangible and intangible property attributes on the popularity scores of PBSAs (reported in Table I). The natural logarithm of the PBSA popularity score is the dependent variable in all the models. Column (1) presents the results for the OLS regressions with the intangible attributes, while Columns (2) and (3) present the results for the OLS regressions with the tangible room-specific and property-specific attributes respectively. Column (4) presents the OLS regression results for the combined tangible attributes (both room-specific and property-specific) and finally, Column (5)- the full (base) model specification combines all intangible and tangible property attributes.

[INSERT Table I]

The results in Column (5) suggest that the intangible attributes of PBSAs are important to students in their online accommodation search. For instance, *ceteris paribus*, an increase in the price of a PBSA by 1% is associated with a 0.74% decline in the popularity score. The other results on rating score, number of reviews, bills composition, rules and distance to the higher institutions further reveal that information provided on tangible property features of PBSAs are important to students in their online accommodation search (generally consistent with findings in Kobue *et al.*, 2017 and Kolawole and Boluwatife, 2016)**.** The results on the effects of reviews particularly suggest that PBSA operators that encourage students to fill out reviews on their properties are likely to see an increase in the number of students that add their properties to the wishlist.

The results on the tangible features show that displaying information on the number of rooms in a property has a negative and significant effect on the popularity score compared to having no information. The results further show that having a private bathroom (relative to having a shared bathroom) increases the popularity of a property, although, having a private kitchen (relative to having a shared kitchen) can make a property less popular. These significant effects contrast with previous studies (such as Khozaei *et al.*, 2011, 2014) and suggest that students may place a higher value on privacy in elements of the building that relate to personal care, whilst simultaneously preferring to share other facilities (such as the kitchen) that foster social interaction.

Properties with coin-operated laundry are found to be 13% less popular on average than properties where laundry is free; and properties with fob/swipe key access are 42% less popular than properties with automated access, while properties with only night patrol are 15% less popular than properties with 24-hour security patrol. The general importance of security to students in their accommodation search is consistent with past studies (such as Khozaei *et al.*, 2011; Kobue *et al.*, 2017; Kolawole and Boluwatife, 2016). The results for room-specific features indicate that having small beds, small double beds and beds of other sizes in a room can increase the property's popularity score, relative to having a double bed in the room. These results may reflect possible concerns by students that bigger beds may decrease space for circulation and other furniture, as well the potentially higher rent for rooms with bigger beds.

4.2 The Effects of Displaying/not displaying Information on Property Attributes on the Popularity Scores of PBSAs

In this section, we analyse the effects of displaying/not displaying information on the PBSA's attributes on the property's popularity. We maintain the same model specification and form in (Table I, Column 5), although all the non-binary variables where some information is not displayed are converted to binary form: (i.e., x=1 if the information on the property attribute is provided; x=0 if this information is not provided). Some attributes, specifically price, number of reviews, bathroom, kitchen and location are displayed on all the properties listed; it is, therefore, impossible to estimate the effects of not displaying their attributes. The results of this empirical exercise are reported in Table II.

[INSERT Table II]

Table II shows that indeed, not displaying a vast majority of the property attributes in our model can make a property less popular which generally aligns with theoretical expectations (similar to Turnball and Sirmans, 1993; Albrecht et. l., 2016; Read, 1993; 1997 and Kim, 1992). For intangible attributes, PBSA properties that display information on ratings, bills and rules are on average more popular, relative to properties that do not display the information. Interestingly, however, properties that display transit time and that there is an onsite manager are on average less popular, although, indicating that there is an onsite manager is not statically significant. For the tangible attributes, we observe that PBSAs with displayed information on laundry, security, cinema room, entertainment area, furniture, number of beds and bed size are on average more popular, although this is not significant for bed size information. In contrast, properties that display the number of rooms in the property, access control and television are less popular, although, this effect is not significant for information on access control and television. We generally do not observe clear differences in information effects between tangible and intangible attributes in our analyses.

The results validate our proposition that not displaying property attributes on a listing platform can adversely affect the booking potential for PBSAs, consistent with the findings of Qiu and Zhao (2018). A possible explanation for this is that students may add a property to their wishlists despite the property listing displaying some attributes which the students do not like, but generally offer a higher level of certainty. There is also the possibility that the point of information on a property listing can attract students, although omitted information can have the opposite effect. For instance, a listing which does not display information on the bathroom may be left off the wishlist, although it may actually have a private bathroom; this attribute, though having the potential to increase the probability of selection, will not have the expected effects because of the failure to list the bathroom information. This can also be exploited by operators who may choose to keep some information off the listing if they believe that providing such information can negatively affect the booking of their property.

4.3 Locational sub-market Analysis

Given the heterogeneity of housing markets by location (see Oladiran *et al.*, 2019), particularly the variation in student accommodation market indicators (Appendix Table I), we disaggregate our analysis by location, using the model specification in Table II (now reported in Appendix Table III, Column 1). Considering that London accounts for about 42% of the overall sample, we estimate a "non-London" model (reported in column 2) to examine whether the results are driven mainly by the London property market. We then estimate a "London-only" model (column 3), and the other regional groups (columns 4-7). We control for the city locations within the sub-samples in all models.

The results for the non-London model (Column 2, Appendix Table III) are not substantially different from those observed in the base model (Column 1, Appendix Table III), although, the model fit decreases from 72% to 45%, suggesting that other unobserved factors may be affecting the popularity score in the non-London cities. We also observe a general decrease in the magnitude of the coefficients in the non-London model, and the coefficient for bills changes from positive to negative, and for TV, it changes from negative to positive, although these variables in the non-London model are statistically insignificant.

In general, we observe a variation in the model fit, magnitude, and statistical significance in the coefficients for the sub-locational models (Columns 3-7 in Appendix Table III). Some effects are however identical across locations. For instance, a higher price will make a property less popular in all the sub-markets, and displaying information on rules, laundry and security can increase the popularity score of a property in all sub-markets. These results validate our proposition that PBSA accommodation preference indicators vary by location, and they are consistent with locational variations typically observed in the residential real estate market. However, some attributes (such as price, rules, laundry, and security) have identical effects across the locational sub-markets.

Additionally, we also create a dummy variable for non-London (i.e., 1=non-London; 0= otherwise) and interact this non-London dummy with every variable in the regression (variable*dummy). This enables us to test whether there are significant differences between the two areas for every variable separately and to test whether the differences between the two areas are significant overall. The coefficients in the model with the location-interaction variables are generally consistent with the base model, suggesting that the effects are identical for properties in London and those outside London.

4.4 Further Robustness Tests and Limitations

We carry out further empirical exercises to examine the robustness and potential biases in our results. The first set of tests examines the sensitivity of our result to the model specification. First, we check for model dependence in our results by estimating a linear hedonic model (Column 2, Appendix Table IV) and comparing the results to the log-linear hedonic base model (Column 1, Appendix Table IV). We do not observe significant variation in both results, suggesting that the estimates are not sensitive to changes in functional form. We also test the robustness of our result by substituting the 1.5 constant which was added to the popularity score with "0.5" and "2.5" in different models before deriving the log; we however did not observe significant variations in the results. Furthermore, we estimate a model without clustering the standard error at the property level (Column 3, Appendix Table IV) and the results show no variation from the results in the base model. We also examine the possibility that the estimates may be biased by the properties with more rooms in the dataset, and we assign the attributes of the first room listed on a property as the room attributes for that property, thus limiting the sample to one room per property (Column 4, Appendix Table IV). Overall, the results for this exercise are similar to our baseline model in terms of sign and significance, although, changes can be observed in the sign of the coefficient for the onsite manager variable, number of rooms in a property, television and furniture, although these attributes are statistically insignificant.

The second set of tests is carried out to examine the commute time from the property to HEI 1 (a proxy for distance). This is important, considering the role of location and distance in previous studies (see Khozaei *et al.*, 2011; Thomsen and Eikemo, 2010). Although the dataset does not capture the distance; we substitute two other “commuting time” variables in the base model. The results show that the sign, magnitude, and statistical significance of the estimated coefficients in the three models are very similar, although a few exceptions can be observed.

Finally, we expand our models to control for several other factors to test for the potential effect of omitted variable bias, considering that the listed PBSAs have a plethora of displayed attributes. Literature has shown that attributes and facilities such as gym, WIFI, elevator etc can affect students’ satisfaction level with a property (Kobue *et al.*, 2017). We, therefore, estimate the base model with the inclusion of these variables. This exercise presents a potential problem of multicollinearity, as most of these attributes have a high correlation. The results (not reported) generally show that these variables are statistically insignificant and their introduction to the model does not improve the model fit, suggesting that these omitted variables may not be essential to students in their online accommodation search. Additionally, we also attempt to control for the type of bedroom. The dataset however contains a few rooms with the indication of room types and overlapping categories in some cases. We, therefore, are unable to include this in the model.

Despite the rigorous empirical analysis and the robustness of the results in this study, some limitations and potential issues are identified. The first issue relates to the use of popularity score as the dependent variable. The cumulative nature of the popularity score suggests that properties that have been listed on the platform for a longer period of time may potentially have a higher number of selections to the wishlist, compared to properties that were recently listed. A potential solution to this problem would be to control for the time that the property has been listed on the platform; however, this information is not available[9].

Furthermore, information on the frequency of changes to listings would have been useful to address the possibility that the information which students took into account when selecting a property to their wishlist is exactly the same as when the data scraping was carried out. However, this information is unavailable. Furthermore, we do not expect operators to make frequent changes to property attributes once they are listed. Thus, it is safe to assume that the information on property attributes at the time of listing is very similar or exactly the same as the information available at data collection. There is also the possibility that properties could manipulate the wishlist data by having employees create accounts and select the properties to their wishlists as is the case in company and products reviews; the time and associated costs of creating an account on student.com may however serve as a deterrent. The second issue relates to the potential effects of the COVID-19 pandemic on students' academic engagement and other health/social policies. Because the automated web scraping exercise was conducted in December 2020, the data may capture COVID-19-related student search patterns which cannot be disentangled. A third potential issue is that the data does not provide information on the distance to the city centre which according to Khozaei *et al.* (2011), Kobue *et al.* (2017), Kolawole and Boluwatife (2016), and Thomsen and Eikemo (2010) is an important element in students' accommodation satisfaction. A fourth issue is potential omitted variable bias. For instance, the aggregate of students' characteristics when the online search was conducted (such as the stage/year of their study and socio-economic, socio-cultural, and demographic factors) could be indicative of the variation in their preference; however, the dataset used for this study does not offer this

[9] Following the wording on the website "for instance, 2045 students saved this property to their wishlist…", our assumption is that these 2045 students are all the users that have put the property on their wishlist as of 17 December 2020 (from the date the property was listed).

information. The role of photographs is also an interesting factor to consider (as shown in Seiler *et al.*, 2012); however, the data scraping technique which we implemented in this study did not capture the picture attributes.

Finally, it should be noted that the sample in this study is selected because the dataset has been restricted to properties in 12 major UK cities on a single online listing platform i.e., student.com. Nonetheless, the results remain robust to several tests including the locational sub-market analysis (in section 4.3) which aimed to identify potential location-specific heterogeneity.

5.0 Summary and Conclusion

This paper analyses the link between the potential demand for purpose-built student accommodation (PBSA) and their online displayed attributes. The paper specifically examines the effects of displaying/not displaying certain property attributes (online) on the popularity score of a PBSA. The data includes information relating to the popularity score, tangible attributes, and intangible attributes of the listed PBSAs in 12 major UK cities obtained from Student.com using an automated cloud-based web-scraper. Using a hedonic framework with a log-linear functional form, we estimate the impact of the online displayed attributes of the properties on their popularity scores.

This study provides useful theoretical and practical insights. The results suggest that students may find properties with less displayed information less attractive, and properties with more displayed information more attractive; these, by extension, can impact the booking potential of an online listed PBSA. We particularly find some negative effects of displaying information on some attributes, suggesting that students may find the information displayed on some attributes to be detrimental. This may become an incentive for PBSA operators to intentionally leave out these attributes on the property listing. These findings particularly shed more light on the application of the search theory to real estate, further extending the work from the traditional residential market (see Qiu and Zhao, 2018) to the student accommodation market. Furthermore, the study provides a unique ex-ante perspective on student accommodation preferences, further adding to already existing ex-post literature (such as Khozaei *et al.*, 2011; Kobue *et al.*, 2017; Kolawole and Boluwatife, 2016; Thomsen and Eikemo, 2010). Additionally, this study makes a valuable contribution to the micro-level student accommodation literature with a larger and more representative sample in the UK context.

With increasing student enrolment numbers, particularly for international students, positive market sentiments and a corresponding high capital flow into the operational real estate sector, particularly to PBSA, PBSA investors will continue to seek ways to maximise their returns. This study provides novel insight that can therefore aid the development of more effective and efficient PBSA investment approaches, particularly for bottom-up investment strategies where investors can identify specific tangible and intangible property features that they should examine carefully and potentially invest in. For instance, investors may wish to consider their property selection strategy more carefully in terms of location (to account for distance to the higher institution) and planning regulations that can influence their ability to provide certain facilities and amenities. Developers should also carefully consider the property attributes that they need to include in their development plans to increase the booking potential of the property. Furthermore, portfolio managers who hold PBSA assets should also identify the property attributes with the highest potential to add value to their assets and maximise portfolio efficiency. Additionally, asset and property managers should develop strategies to ensure optimal asset performance by identifying the property attributes that their marketing should highlight and emphasise when listing their properties online.

For further research, the scope of this study can be expanded to other geographical contexts, possibly with perspectives on how these property attributes relate to the listed prices. It will also be useful to examine the factors explored in this paper using booking (where available) to provide a better measure of demand. Furthermore, the application of consumer behaviour and search theories to students' housing choices can be further explored to gain deeper insight into the decision making and the search and selection process; the effects of photographs will particularly be an interesting area to further explore.

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Table I: Base Models (Log Popularity score): OLS Regression Estimates

		(1)	(2)	(3)	(4)	(5)
	VARIABLES	Non-tangible	Tangible House/property	Tangible Room	Tangible- House and room	Full spec-tangible and non-tangible
Non-Tangible features	Log of Price	-0.662***	NO	NO	NO	-0.744***
	Rated between 1 and 1.99	-	NO	NO	NO	-
	Information not provided	-0.649***	NO	NO	NO	-0.683***
	Rated between 2 and 2.99	0.351***	NO	NO	NO	0.0175
	Rated between 3 and 3.99	0.663***	NO	NO	NO	0.256**
	Rated between 4 and 4.99	0.657***	NO	NO	NO	0.367***
	Rated 5*	0.325***	NO	NO	NO	0.0877
	Number of Reviews	0.00863***	NO	NO	NO	0.00640***
	All bill inclusive	-	NO	NO	NO	-
	Information not provided	-3.248***	NO	NO	NO	-1.123***
	Some bills included	0.00266	NO	NO	NO	0.106*
	Alcohol and smoking prohibited	-	NO	NO	NO	-
	Information not provided	-0.560***	NO	NO	NO	-0.362***
	Only one of alcohol or smoking prohibited	-0.00640	NO	NO	NO	-0.0531
	Having an onsite manager	0.234***	NO	NO	NO	-0.0235
	30 or more minutes to transit to HEI 1	-	NO	NO	NO	-
	Information not provided	0.317**	NO	NO	NO	0.291**
	Less than 10 minutes	0.135	NO	NO	NO	0.0842
	10-19 minutes	0.118	NO	NO	NO	0.124
	20-29 minutes	0.134	NO	NO	NO	0.265*
Tangible features (house/property)	Information on number of rooms in the house	NO	0.372***	NO	0.0435	-0.168***
	Private bathroom	NO	0.905***	NO	-0.412***	0.475***
	Private kitchen	NO	-0.216***	NO	-0.333***	-0.186***
	Laundry operation is free	NO	-	NO	-	-
	Information not provided	NO	-1.433***	NO	-0.944***	-0.706***
	Laundry coin operated	NO	-0.157**	NO	-0.0799	-0.134*
	Automated access control	NO	-	NO	-	-
	Information not provided	NO	-0.658***	NO	-0.651***	-0.0705
	Access with fob/swipe key	NO	-1.582***	NO	-1.235***	-0.422***
	24- hour patrol	NO	-	NO	-	-
	Information not provided	NO	-0.830***	NO	-0.767***	-0.525***

	Night patrol only	NO	-0.173***	NO	-0.190***	-0.150***
	Cinema Room	NO	0.428***	NO	0.366***	0.351***
	Entertainment Area	NO	0.595***	NO	0.340***	0.237***
	Television	NO	0.0860	NO	0.103*	0.0126
Tangible features (room specific)	Chair, desk and closet available	NO	NO	-	-	-
	Information not provided	NO	NO	-0.00782	-0.0493	-0.00281
	1 or more piece of furniture in the room	NO	NO	0.304	0.0201	0.0647
	1 bed per in one room	NO	NO	-	-	-
	Information not provided	NO	NO	-3.551***	-2.083***	-1.228***
	2 or more beds in one room	NO	NO	-0.150	0.0538	0.332***
	Double bed in room	NO	NO	-	-	-
	Information not provided	NO	NO	-0.138	0.0640	0.0641
	Small bed	NO	NO	0.728***	0.604***	0.308***
	Small double	NO	NO	0.474***	0.232***	0.0901**
	Other sizes	NO	NO	-0.0841	-0.00864	0.424***
Location Fixed effects	London	-	-	-	-	-
	Birmingham	-0.667***	-0.120**	-0.321***	-0.336***	-0.795***
	Bristol	-1.766***	-1.273***	-1.102***	-1.493***	-1.849***
	Cardiff	-0.260***	0.121	-0.396***	-0.0324	-0.593***
	Edinburgh	-0.665***	0.0484	-0.0609	-0.141*	-0.580***
	Glasgow	-0.817***	3.32e-05	0.227***	-0.0615	-0.879***
	Leeds	-1.038***	-0.727***	-0.562***	-0.811***	-1.209***
	Leicester	-1.601***	-0.969***	-1.352***	-1.201***	-1.646***
	Liverpool	-1.538***	-1.146***	-1.100***	-1.289***	-1.764***
	Manchester	-0.743***	-0.220**	-0.660***	-0.532***	-0.782***
	Nottingham	-0.518***	-0.257***	-0.419***	-0.442***	-0.692***
	Sheffield	-1.005***	-0.583***	-0.537***	-0.732***	-1.175***
	Constant	8.961***	6.149***	4.985***	6.202***	10.04***
	Observations	4,195	4,195	4,195	4,195	4,195
	R-squared	0.670	0.588	0.468	0.657	0.735

Notes: Standard errors clustered at property level; *** p<0.01, ** p<0.05, * p<0.1

Table II: Models Estimating Effects of Displaying (vs not displaying) Information on Property Attribute (Log Popularity score): OLS Regression Estimates

		(1)
	VARIABLES	All cities
Non-tangible features	Log of Price#	Yes
	Rating information	1.008***
	Review#	Yes
	Bill information	1.316***
	Rules	0.363***
	Having an onsite manager	-0.00834
	Transit time	-0.212***
Tangible features (property)	No of rooms in property	-0.165**
	Private Bathroom#	Yes
	Private Kitchen#	Yes
	Laundry	0.610***
	Access	-0.0560
	Security	0.429***
	Cinema Room	0.275***
	Entertainment Area	0.242***
	Television	-0.00873
Tangible features (room)	Furniture	0.0966**
	No of beds in room	1.314***
	Bed size	0.00597
	Location#	Yes
	Constant	5.094***
	Observations	4,195
	R-squared	0.724

Notes: Standard errors clustered at property level; *** p<0.01, ** p<0.05, * p<0.1. #*The variable retains its original form as in the base model because it does not contain missing information*

Appendices

Appendix Table I: Aggregate Values of Key Property Features across Cities

	City	Number of rooms	Number of properties	Average Number of rooms per property*	Mean Price	Mean Popularity score (based on property)
1	Birmingham	268	53	10	£158	160
2	Bristol	49	12	6	£202	101
3	Cardiff	162	21	11	£132	169
4	Edinburgh	144	20	9	£181	212
5	Glasgow	244	39	8	£141	266
6	Leeds	158	38	6	£156	146
7	Leicester	242	52	8	£173	71
8	Liverpool	276	50	9	£127	128
9	London	1773	552	9	£282	146
10	Manchester	353	82	7	£169	183
11	Nottingham	182	34	12	£150	182
12	Sheffield	344	55	9	£121	219
Total (all cities)		**4195**	**960**	**9**	**£206**	**156**

*Note: *Aggregated to the nearest whole number*

Source: *Authors' Illustration, 2022 (using data from student.com)*

Appendix Table II: Summary Statistics

Variable name	Variable Description	Obs	Mean	S.D
Price (rent per week)	Log of rent of the room per week	4195	5.208	0.445
Rating				
No rating	Binary variable=1 if the property does not have any rating information, zero otherwise	4195	0.4772	0.4995
One Star	Binary variable=1 if the property rating is between 1-1.99, zero otherwise	4195	0.0105	0.1019
Two Star	Binary variable=1 if the property rating is between 2-2.99, zero otherwise	4195	0.0319	0.1759
Three Star	Binary variable=1 if the property rating is between 3-3.99, zero otherwise	4195	0.1087	0.3113
Four Star	Binary variable=1 if the property rating is between 4-4.99, zero otherwise	4195	0.3066	0.4611
Five Star	Binary variable=1 if the property rated 5, zero otherwise	4159	0.0651	0.2467
Reviews	Continuous variable: measuring the number of reviews that have been written on a property	4195	7.299	15.685
Bills included in rent				
No information	Binary variable=1 if no information provided on bills included in the rent, zero otherwise	4195	0.1066	0.3086
Some Bills	Binary variable=1 if some bills not all are included in the rent, zero otherwise	4195	0.7650	0.4241
All Bills	Binary variable=1 if information is provided to indicate that all bills (water, electricity, heating, gas, WiFi, content insurance and cleaning services) are inclusive, zero otherwise	4195	0.1285	0.3347
Rules (Alcohol and Smoking)				
No information	Binary variable=1 if no information provided on rules, zero otherwise	4195	0.5013	0.5001
Some Prohibition	Binary variable=1 if information is provided on either smoking or alcohol prohibition, but not both, zero otherwise	4195	0.3812	0.4857
Full Prohibition	Binary variable=1 if information is provided to indicate that both alcohol and smoking are prohibited within the property, zero otherwise	4195	0.1175	0.3221
Onsite manager	Binary variable=1 if information is provided that there is an onsite manager, zero otherwise	4195	0.368	0.482
Transit time to closest HEI				
No information	Binary variable=1 if there is no record of the transit time and zero otherwise	4195	0.2074	0.4055
Less than 10mins	Binary variable=1 if transit time is less than 10 minutes, zero otherwise	4195	0.2777	0.4479
Between 10-19mins	Binary variable=1 if transit time is between 10 and 19 minutes, zero otherwise	4195	0.4715	0.4992
Between 20-29mins	Binary variable=1 if transit time is between 20 and 29 minutes, zero otherwise	4195	0.0341	0.1815

More than 30mins	Binary variable=1 if transit time is more than 30 minutes, zero otherwise	4195	0.0093	0.0960
Number of rooms in flat	Binary variable=1 if no information is provided on number of rooms, zero otherwise	4195	0.980	0.297
Bathroom use	Binary variable=1 if private bathroom, zero if shared bathroom	4195	1.233	0.423
Kitchen Use	Binary variable=1 if private kitchen, zero if shared kitchen	4195	0.303	0.460
Laundry				
No information	Binary variable=1 if there is no information on the laundry operation, zero otherwise	4195	0.2741	0.4461
Free Laundry	Binary variable=1 if laundry operation is free, zero otherwise	4195	0.0732	0.2605
Coin operated	Binary variable=1 if the laundry is coin operated, zero otherwise	4195	0.6527	0.4762
Access Control				
No information	Binary variable=1 if there is no information on the access control, zero otherwise	4195	0.3788	0.4851
Controlled Access	Binary variable=1 if there is controlled access, zero otherwise	4195	0.5037	0.5000
Swipe key card	Binary variable=1 if access is with a fob or swipe key/card, zero otherwise	4195	0.1175	0.3221
Security				
No information	Binary variable=1 if there is no information about security, zero otherwise	4195	0.6791	0.4669
24-hour patrol	Binary variable=1 if there is 24-hour patrol, zero otherwise	4195	0.1986	0.3990
Night only	Binary variable=1 if night patrol only, zero otherwise	4195	0.1223	0.3277
Number of beds in Bedroom				
No information	Binary variable=1 if there is no information about number of beds and zero otherwise	4195	0.1094	0.3122
One bed	Binary variable=1 if there is only one bed and zero otherwise	4195	0.8284	0.3771
More than one bed	Binary variable=1 if there is more than one bed and zero otherwise	4195	0.0622	0.2416
Room Furniture	Binary variable=1 if there is at least a furniture in the bedroom and zero otherwise	4195	0.5502	0.4975

Source: *Authors' Illustration, 2022 (using data from student.com)*

Appendix Table III: OLS Regression Estimates with Locational sub-markets (Log Popularity score): displaying information vs not displaying information.

		(1)	(2)	(3)	(4)	(5)	(6)	(7)
	VARIABLES	All cities	Non-London	London	Midlands	South Eng/Wales	Scotland	Northern England
Non-tangible features	Log of Price#	-0.736***	-0.767***	-0.673***	-0.451**	-1.096*	-0.699***	-0.428***
	Rating	1.008***	0.829***	1.401***	0.515***	1.081***	0.426***	1.139***
	Review#	0.00850***	0.00930***	0.000422	0.00555***	-0.00605	0.0211***	0.00957***
	Bills	1.316***	-0.260	1.337***	0.287	-0.290	NO	-1.505***
	Rules	0.363***	0.553***	0.0163	0.0826	0.707**	0.193***	0.938***
	Onsite Manager	-0.00834	-0.0684	0.199***	-0.223***	0.576**	0.440***	-0.0785
	Transit time	-0.212***	-0.300***	-0.120*	0.0521	-0.745***	-0.0575	-0.489***
Tangible features (property)	No of rooms in property	-0.165**	-0.336***	0.333***	0.137	0.124	-0.128	-0.414***
	Private bathroom#	0.419***	0.410***	0.210***	0.517***	0.00480	-0.163	0.296**
	Private kitchen#	-0.237***	-0.190***	-0.285***	0.0148	-0.306***	0.111*	-0.345***
	Laundry	0.610***	0.405***	0.681***	0.664***	0.520***	0.0798*	0.237**
	Access	-0.0560	-0.0777	0.0819	0.302***	-1.182***	-0.132	-0.147
	Security	0.429***	0.239***	0.709***	0.448***	0.724**	0.269***	-0.173**
	Cinema Room	0.275***	0.365***	0.0887	-0.135	0.262**	-0.0271	0.692***
	Entertainment Area	0.242***	0.125**	0.426***	0.203**	0.0275	0.0945	0.101
	Television	-0.00873	0.0498	0.0890	0.109	-0.493***	-0.00159	0.0244
Tangible	Furniture	0.0966**	0.119**	0.0553	-0.221**	-0.162	0.133**	0.211**
	No of beds in room	1.314***	0.185	1.235***	0.267	NO	0.105	0.344
	Bed size	0.00597	0.00616	0.0156	0.0421	-0.737***	-0.0252	0.385*
	Location FE#	Yes	Yes	-	Yes	Yes	Yes	Yes
	Constant	5.094***	7.431***	4.515***	5.080***	10.19***	8.010***	5.429***
	Observations	4,195	2,422	1,773	692	211	388	1,131
	R-squared	0.724	0.453	0.856	0.564	0.652	0.602	0.433

Notes: Standard errors clustered at property level; *** p<0.01, ** p<0.05, * p<0.1

#*The variable retains its original form as in the base model because it does not contain missing Information.*

-The variable- "number of beds in room" has no missing information in Cardiff and Bristol, hence no coefficients are reported for that variable in column 5; and the variable "bills" has no missing information for Scotland.

Appendix Table IV: OLS Regression Estimates (Log Popularity score): base

model and other specifications- displaying information vs not displaying information.

		(1)	(2)	(3)	(4)
	VARIABLES	Base model (log Y)	Linear Model	No cluster (log Y)	One room only (log Y)
Non-tangible features	Log of Price	-0.736***	-160.1***	-0.736***	-0.889***
	Rating information	1.008***	155.3***	1.008***	1.065***
	Review	0.00850***	3.965***	0.00850***	0.0101***
	Bill information	1.316***	77.64***	1.316***	0.838***
	Rules	0.363***	71.24***	0.363***	0.287***
	Having an onsite manager	-0.00834	46.14***	-0.00834	0.142
	Transit time	-0.212***	-11.62	-0.212***	-0.141
Tangible features (property)	No of rooms in property	-0.165**	-25.12*	-0.165***	0.255
	Private bathroom	0.419***	36.11***	0.419***	0.999***
	Private kitchen	-0.237***	-41.36***	-0.237***	-0.166
	Laundry	0.610***	72.80***	0.610***	0.610***
	Access	-0.0560	-39.59***	-0.0560	-0.00200
	Security	0.429***	107.0***	0.429***	0.373***
	Cinema Room	0.275***	92.36***	0.275***	0.303***
	Entertainment Area	0.242***	48.13***	0.242***	0.262***
	Television	-0.00873	-64.81***	-0.00873	0.164
Tangible features (room)	Furniture	0.0966**	67.56***	0.0966**	-0.209**
	No of beds in room	1.314***	126.1***	1.314***	1.219***
	Bed size	0.00597	-6.812	0.00597	0.0216
Location FE	City	Yes	Yes	Yes	Yes
	Constant	5.094***	879.8***	5.094***	5.731***
	Observations	4,195	4,195	4,195	960
	R-squared	0.724	0.602	0.724	0.782

Notes: Standard errors clustered at property level; *** p<0.01, ** p<0.05, * p<0.1