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Estimating small-area demand of urban tourist for groceries: the case of Greater London

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Abstract Tourist retail demand within urban areas brings both opportunities and challenges to the local economy. Taking Greater London as the study area, this paper integrates conventional statistics and survey datasets with novel crowdsourcing big data sources to identify and estimate four types of tourist grocery demand at the small-area scale: travellers staying with Airbnb, tourists using traditional commercial accommodation, guests staying with relatives or friends and day trip visitors. Based on this combined tourist retail demand layer we show the spatial variations at the small area level and, as an illustration of the demand uplift, we estimate additional grocery expenditure that is associated with this tourist demand. Thus, the paper indicates the neighbourhoods with significant grocery demand uplift from tourist stays. We argue that the new retail demand layer has tremendous potential to be used as an additional input to retail location modelling tools to support new store revenue estimation and store performance evaluation within the grocery retail sector.

Keywords: Small-area demand estimation; Grocery retail; Urban tourist; Airbnb; Greater London

1. Introduction

Spatial models are important tools in retail location planning, especially within the UK grocery sector. A major step in the modelling process is the estimation of retail demand within small-areas in order to then predict individual store revenues and trading potential. The estimation of small-area retail demand has traditionally been residence-based, using population data from censuses coupled with expenditure data from surveys such as the UK Office for National Statistics (ONS) Living Costs and Food Survey. Usually, that census data can be disaggregated to estimate demand by age, social class, ethnicity etc. (Birkin et al., 2017). However, for areas that have a more complex population composition, demand estimation may not be adequately captured using residence-based demand alone. Recent work has started to shed light on other essential drivers of retail demand, covering populations of work-based consumers in major cities (Berry et al., 2016), school and university students (Waddington et al., 2019), and tourists at coastal resorts (Newing et al., 2015). However, for towns and cities also hosting large volumes of tourists, it is rare to see any consideration of the potential uplift in retail demand from these consumers. One of the reasons why this has been under-researched to date is the lack of effective fine-granularity datasets related to tourist travel behaviour and expenditures, especially at the small area level.

As one of the world's most visited destinations, London attracted 19.1 million international tourists in 2018 alongside 11.9 million domestic visitors (VisitBritain, 2019; VisitEngland, 2018). These visitors generated spending estimated at £12.33 million and £2.98 million respectively (VisitBritain, 2019; VisitEngland, 2018). Whilst the UK International Passenger Survey and Great Britain Tourism Survey provide monthly data on visitor numbers and spending, little is known about the distribution of these tourists or their economic impact at the local level.

Tourists and day visitors make up over 10% of the daytime population in London, which brings both tremendous opportunities and challenges for the local economy (Greater London

Authority (GLA), 2014). Also, for tourists staying within London overnight, previous studies have recognised that a large share of their time is spent in the immediate vicinity around their accommodation locations (Shoval et al., 2011). Grocery stores are not usually located purely to serve tourists but many individual stores may be impacted by tourism. However, tourist or visitor expenditures on groceries, much of which take place at a local level, are rarely recalled in sample-based surveys of tourist expenditures. Therefore, this paper aims to estimate the demand from tourists and day visitors for groceries in London at the small-area scale. Aligning with the International Passenger Survey and Great Britain Tourism Survey definitions, we identify four groups of prominent tourists in London: visitors using the sharing-economy accommodation platform Airbnb; tourists staying at hotels and other serviced accommodation (i.e. B&Bs, guest houses, motels and hostels); 'free' guests who spend their nights with relatives or friends; and day trip visitors who only undertake leisure activity-based trips during the day/evening without using overnight accommodation.

Since there is little information from existing surveys concerning the spatial distribution of these four groups, we explore the potential offered by novel big datasets (principally from Airbnb and Twitter) when combined with conventional official statistics and survey datasets. The Airbnb listing and reservation records (available at the property level) offer new insights into the distribution and occupancy rates of their guests. In addition, user-generated crowdsourced data (such as those extracted from geotweets) could enable detailed space-time modelling at the individual level to help capture the distribution of day trip visitors, who are not captured by accommodation-based measures of tourism.

Thus our aim in this paper is to estimate the small-area grocery demand of each of the four tourist groups at a neighbourhood level and to incorporate them into a final tourist grocery demand layer for London. It is argued that the additional demand from these types of tourism is substantial and produces a significant uplift of expenditure (and hence revenues) across many localities in London, some of which are not traditionally associated with tourism activity. We argue that the incorporation of tourist retail demand into the spatial modelling process has the potential to enhance retailers' managerial decision-making in two major ways. First, it is important retailers understand more about the type of shoppers who frequent different stores. This can have implications for local marketing, store promotions and local stock provision. Second, it is especially important in estimating revenues for future stores. Forecasts of future revenues based purely on residential demand may not provide the necessary profit to make a store economically viable and hence the retailer may miss an important opportunity for growth. The inclusion of tourist demand may take revenues beyond the threshold needed for long-term store viability.

The rest of the paper is structured as follows. In Section 2, we review the existing literature on small-area retail demand estimation in location planning, particularly for non-residential populations. We argue that small-area tourist demand estimation, in the context of urban tourism, is far under-researched and that location-based online big data can effectively act as an important data source for tourist activities and consumer behaviour. Section 3 details the datasets used in our research. In Section 4 we estimate the potential grocery expenditure of each of the 4 groups. The final, combined, tourist retail demand layer in London is illustrated and discussed in Section 5. Finally, Section 6 offers some concluding comments. Throughout the paper we use the UK grocery market, and specifically London, as our case study.

2. Literature review

2.1 Retail demand in location planning

The estimation of small-area retail demand is important in its own right but is also crucial when constructing retail location planning models. The standard approach is to combine small area population census statistics with market survey data (in the UK from sources such as the Living Costs and Food Survey) which gives average weekly household expenditures for a variety of retail goods and services. For the production of more realistic spatial models, retail demand is usually disaggregated by person type (to take account of different types of consumer behaviour) including gender, age, ethnicity, social class/ income. Based on the effective simulation of residential demand, it is possible to apply these demand side estimations within spatial models to facilitate retail location planning (Birkin et al., 2017).

Due to the ongoing collaboration between academia and a growing number of major UK retailers, valuable commercial big datasets, including store trading records and loyalty card scheme data, are becoming more accessible to the academic community for research purposes. These corporate datasets have already been used to validate the success of store revenue forecasts in traditional models which focus substantially on residential demand (Lovelace et al., 2016). Newing et al. (2013a) demonstrated the possibility of adding non-residential retail demand into spatial models (in this case adding seasonal visitor demand around coastal tourist resorts in Cornwall, a coastal region in south west England that receives significant tourism) using newly available customer-level loyalty card sales data provided by a partner retailer. This provided valuable new information for store location planning. They identified that the proportion of trade accounted for by non-residents in one case study coastal store varied from a peak of 50% in August to only 12.5% in January. Without such detailed estimations, the prediction of store revenues within such tourist areas in peak seasons has often been underestimated by retailers. It is very difficult to simply upscale residential demand consistently to obtain accurate demand-side or individual store revenue estimates (Newing et al., 2014). Subsequently, Berry et al. (2016) identified workplace and commuter-derived trade from retail partner transaction records at a number of convenience stores in London. They noted that these stores exhibit huge temporal spikes in sales of 'food to go' products, especially when in close proximity to major employment centres or transport interchanges. Waddington et al. (2017) demonstrated that a conventional residential-based retail model works poorly when attempting to estimate the revenues for convenience stores located in catchments containing workplaces or which are in proximity to universities, colleges or large secondary schools. These areas have a more diverse demand than stores serving a predominantly residential demand and these stores thus exhibit a sales pattern which may reveal noticeable demand uplift associated with these different drivers of demand (often at different times of the day/week).

In the above-mentioned papers, the distribution of the subgroups is still mainly based on static census-derived statistics and bespoke survey datasets. For example, Berry et al. (2016) used census-derived workplace population statistics to understand the micro geographies of workplace demand. Waddington et al. (2017) disaggregated non-residential retail demand into four different drivers: workers, school children, university students and daytime visitors. In common with Berry et al. (2016) they made use of workplace population statistics to capture the workplace population, supplementing these estimations with data from administrative and survey sources to capture demand associated with schools, universities and principal tourist attractions. In the case of coastal tourist demand, Newing et al. (2013a) explored the linkage between tourist grocery demand and the distribution of self-catering accommodation at the small area level. They used listings of self-catering tourist accommodation, in conjunction with surveyed occupancy rates, to estimate the small area spatiotemporal distribution of tourists as a demand-side input to a retail location model (Newing et al., 2013b).

Estimating the expenditure rates of the non-residential population is also a major challenge, since rarely can such expenditure rates be directly sourced. For example, after discussion with industry representatives, Waddington et al. (2019) incorporated an expenditure of £5 per person per week as the workplace-derived expenditure on groceries, while the school- and university-based expenditure were allocated £3.50 and £1.50 per person per week respectively, according to available consumer research in ad-hoc surveys. For the estimation of visitor demand in Cornwall, Newing et al. (2013b) collected data from a variety of organisation reports, industry surveys and academic research related to the self-accommodation hospitality sectors in the UK to estimate the different spending rates of visitors staying at different types of accommodation.

These studies highlight that store trading records and customer-level loyalty card data can provide evidence of the links between store sales and spatiotemporal demand fluctuations in a catchment area, driven by the ebbs and flows of transient populations within the region. They also highlight that little is known about the expenditure patterns of non-residential demand types and that both academic and industry research have to rely on (often incomplete) ad-hoc surveys and insight to infer expenditures associated with these demand sub-groups. We argue in this paper, in relation to urban tourist demand, that a bottom-up approach is useful in order to construct a comprehensive tourist-based demand surface. This involves aggregating the estimated expenditure of each demand subgroup, accounting additionally for their spatial and temporal distributions.

2.2 Urban tourism and big data

As noted above, there is a deficiency of official tourism statistics at a disaggregate spatial scale. This presents a number of challenges for tourist population modelling. However, big data is beginning to help fill that gap. There are two major types of big data which can be valuable in tourist research. The first is user-generated content from location-based social media (i.e. geotagged tweets, geo-photos, and reviews of point-of-interests (POIs) etc.). Such data are beginning to enable space-time modelling at the individual level and have been used to assess international mobility patterns (Barchiesi et al., 2015), monitor visitor behaviour around tourist attractions (Tenkanen et al., 2017), identify tourist hotspots in cities (Kádár, 2014) and to characterise tourist flows within destinations (Chua et al., 2016). The academic community has started to leverage these emerging big data sources as important supplements to conventional statistical sources. This enables fine-scaled spatiotemporal patterns of tourist distributions to be uncovered (comprehensive reviews appear in Li et al., 2018, Ye et al., 2020). Such studies are shedding new light on the role that emerging location-based big data could offer in helping to outline the spatial distribution of tourists, but none has focused so far on the use of this data to provide more nuanced local retail expenditure estimates. The second big data source covers tourist accommodation. The location of tourist accommodation has a profound impact on tourist movements and can impact greatly on service providers that are in the catchment area of these accommodations. These include data sources such as AirDNA which provides data on the growing use of Airbnb. This dataset is beginning to be used in tourist studies more widely (Gutiérrez et al., 2017). We shall examine both these types of data more fully in the next section before using them to estimate retail demand in later sections.

3. Data and methodology

To fully understand tourist grocery demand at the small-area level, we need to capture tourists who stay in London using a range of different accommodation types. These first include the rapidly growing sharing economy platform Airbnb. Primarily drawn from the existing housing stock, Airbnb has become a popular alternative to traditional accommodation, enabling tourists to have distinctive and more local experiences at their destination (Greater London Authority, 2017). This research uses a big dataset supplied by AirDNA and accessed via the Consumer Data Research Centre (CDRC) at the University of Leeds. The AirDNA dataset enables us to retrieve all the Airbnb listing and reservation records in London for a 12-month period: here we access data between June 2017 and June 2018. The accommodation capacity of the Airbnb properties, coupled with reservation records, is used to delineate the spatial distribution of Airbnb rental units, identify typical occupancy rates and thus calculate the number of local Airbnb guests during the one-year time span.

In addition, it is important to look at the more traditional accommodation sectors. According to the International Passenger Survey (2019) and the Great Britain Tourism Survey (2019) (Table 1), for both overseas and domestic tourists, the two main accommodation types are serviced commercial accommodation (hotel/guest houses, bed & breakfast, hostel/university/school) and free guest/ home tourists staying with relatives or friends in their own houses. Since individual establishment level data related to the provision of serviced commercial accommodation is hard to access from any official channel, we have generated a dataset derived from the combination of Ordnance Survey Point of Interest (POI) data and OpenStreetMap. As a result, a total of 2,042 geo-located serviced accommodation establishments in London have been identified and extracted from those sources.

Whilst Table 1 shows that we have estimates of the total number of people staying with friends, there is no definitive source which records the location of these visits. The simplest approach to generate this data would be to distribute known numbers of these tourists/guests across all residential areas of London pro rata to their population size. For domestic visitors that makes sense. However, it is more likely that international visitors would stay with relatives or friends who share a similar country of birth or ethnic origin: for example, witness the great concentration of Australian tourists and visitors around Earl's Court in London. Although this will not always be the case we feel this method of allocation to residential areas makes more sense than an even distribution across all areas of London. We can plot the residential population by country of origin (derived from 2011 Census-based statistics), and link this to data on international tourists by country of origin/ethnicity provided by the UK International Passenger Survey (see Section 4 below).

Another overlooked tourist group who may also impact upon local retail demand is day visitors. In a daytime population survey by the Greater London Authority in 2014, they categorise day visitors as '3 Hour + Leisure Day Visitors'. In addition, the Great Britain Day Visits Survey (2018) notes that these visits are distinguished by 'visitors not undertaking activities that would regularly constitute part of their work or would be a regular leisure activity'. Day visitor statistics at the London borough level are available via the Greater London Authority daytime population survey (unfortunately no fine-scale statistics are available). Thus we need to spatially redistribute those borough level day visitor estimates across the Lower Super Output Areas (LSOAs) within each respective borough. To do this we can estimate the levels of tourist/leisure activity in different LSOAs using another big data source – geotagged Tweets (geotweets) from the popular social networking service Twitter. We collect geotweets within our London study area from Oct. 2018 to Sept.2019 which occurred between 9 am and 5 pm (daytime geotweets). By tracing back the historical geotweets of these Twitter users, we can usually infer their countries of origin. The modelling of day visitor distributions only leverages geotweets from UK domestic Twitter users. Day visitor activity is distinguished from activity around the usual residence of a user by examining the frequency of tweets – more than 10 geotweets per user at a particular location during our data collecting timespan would suggest a home location. The day visitor count in each borough is distributed across its constituent LSOAs according to the proportion of geotweets in each of those LSOAs.

For each of the four types of tourists outlined above, we plot the spatial pattern of their distributions across the LSOAs in London in Section 4. Then we estimate the average personal expenditure rate per week of each tourist type (for grocery shopping). The resultant small-area tourist grocery demand layer across London is thus generated by the combination of these four demand groups. The datasets employed in the research are summarised in Table 2 and the appendix gives a web link for accessing these data sets directly.

4. Estimating tourist grocery demand

4.1 Airbnb guest

As a new form of commercial self-catering accommodation, Airbnb guests can dine out or purchase and prepare their own food in-house. Airbnb (2018) reported an average expenditure of £100 per guest per night from their international guests in the UK, with an average 10% spent on groceries and 33% spent on food and drink eaten in other establishments. Additionally, 43%

of the £100 is spent in the neighbourhoods in which they stay Airbnb (2018). Therefore, we may expect a substantial uplift of revenue for the grocery stores in the localities that host many Airbnb guests. In the absence of any other survey data for now we use the £10 per guest per day reported by Airbnb (2018) as the average grocery spending rate of an Airbnb guest. It is plausible that the actual rate in London would be typically higher on a per-person per night-basis than comparable stays elsewhere in the UK, given that London accounts for 41.7% of all overnights visit but 53.8% of inbound tourist expenditure in the UK (VisitBritain, 2019).

Figure 1 shows the accommodation capacity of Airbnb listings aggregated into neighbourhoods (LSOAs) across London. In common with all forms of accommodation, it shows a centralisation of accommodation stock within central London where many of the main tourist attractions are located. However, compared to the hotel distribution across LSOAs in London (Figure 3), Airbnb accommodation is far more widely dispersed, including within many residential areas that are not traditionally associated with tourism activity.

To depict the spatial distribution of occupied Airbnb premises (and therefore the presence of tourists), we use the reservation records of each Airbnb listing during the 12-month period to obtain the actual utilisation of the Airbnb properties in London. For all the 207,117 properties listed on AirDNA, only 51.65% (106,974) have online reservation records between June 2017 to May 2018, accounting for 24.6m guest nights. The remainder represents listings that appear not to have received paying guests, at least not via Airbnb. Combining accommodation capacity and the occupancy rate for these properties, alongside an average grocery expenditure of £10 per guest per day, the estimated Airbnb guest grocery expenditure per week across the LSOAs in London totals a considerable annual demand uplift of £246.2m, or £4.72m per week. The spatial distribution of this additional tourist-driven spend is presented in Figure 2. The spatial pattern of Airbnb grocery demand in inner London presents a similar pattern to the distribution of capacity in Figure 1, but some Airbnb properties in outer London generate low demand due to low recorded occupancy. Nevertheless, Figure 2 illustrates that Airbnb properties generate tourist grocery expenditures which are distributed across Greater London and not solely associated with core central London tourist hotspots.

4.2 Hotel and commercial accommodation traveller

The Accommodation Stock Audit conducted in 2016 reported serviced and non-serviced accommodation provision at the borough level across London (VisitEngland, 2016), which is the finest spatial resolution source of published data relating to traditional commercial accommodation provision (Table 3). We assume that most of the non-serviced accommodation are listed as Airbnb properties and have therefore already been captured by the Airbnb dataset discussed above. Therefore, in this section we specifically consider expenditures associated with tourists staying within serviced commercial accommodation. By combining data from the Ordnance Survey POI and the OpenStreetMap, we obtained the locations of 2,314 serviced accommodation establishments in London. The Accommodation Stock Audit gives the number of rooms or bed space for each London borough which we disaggregate evenly across LSOAs in each borough. Figure 3 maps the estimated bed space counts for serviced accommodation across the LSOAs in London. Most are centrally located as expected, but the patterns clearly show a cluster of accommodation near Heathrow Airport to the far west of London.

The actual utilisation of the serviced commercial accommodation stock can be estimated by multiplying the number of bed spaces by headline published occupancy rates for serviced accommodation. According to VisitEngland (2019), the annual average bed space occupancy of serviced accommodation in 2019 in London is 60.3%, i.e. on any given night approximately 60% of bed spaces are occupied and thus have potential to generate grocery expenditures. Clearly this will be higher in the summer months but since London is subject to fewer seasonal peaks in tourism than other destinations in the UK, we do not consider seasonal pattern analysis in this paper. Tourists staying in serviced accommodation rarely have cooking facilities provided and therefore will not be major purchasers of groceries. Their grocery shopping behaviour is thus more likely to be similar to workplace populations, who typically purchase snack food items to go (Berry et al., 2016). Therefore, in the absence of any more comprehensive survey data or insight into these tourist expenditures, we deem it sensible to use the same £5 per person as the average groceries expenditure (per week) associated with a typical non-residential worker (Waddington et al., 2017). Using this method, the grocery expenditure of serviced accommodation tourists in London is estimated at £1.35m per week. The spatial distribution of this additional grocery expenditure is shown in Figure 4.

4.3 Free guest/own home

Guests staying with relatives or friends is another major form of accommodation in London, whose economic impact has been largely overlooked (Shani and Uriely, 2012; Backer, 2007). As Table 1 illustrates, 27.2% of the inbound tourist visits in London are made by guests staying with their relatives or friends, making up for 38.5% of all inbound tourist nights. Domestic visitor numbers in London are even higher – around 40% of the trips are registered as staying at a friend or relative's home, accounting for 48.7% of domestic tourist nights in London. Inbound tourists and domestic visitors generate around 19% and 17% respectively of the total spend in London, but how these visitors impact the local economy at the small-area level is an issue that is rarely examined (International Passenger Survey, 2019; Great Britain Tourism Survey, 2019). Guests staying with local residents are likely to generate a further uplift to local grocery demand.

Table 4 lists the total night stay of international and domestic guests in London. Using this International Passenger Survey data we now allocate the total nights in London of each country across the LSOAs according to the distribution of the usual residents in the corresponding ethnic group (as described above). Thus, we first assign each country of origin to the corresponding ethnic group.

All 38 countries listed can be grouped into 20 ethnic census groups, as shown in the last column of Table 4. The 14 European countries (France, Spain, Germany, Netherlands, Switzerland, Hungary, Portugal, Belgium, Sweden, Norway, Czech Republic, Austria, Finland and Luxembourg) can be categorised as "European Mixed" ; Polish, Irish, Italian and Greeks can be kept as unique ethnic groups; USA and Canada can be combined as "North American"; UAE and Saudi Arabia as "Arab", and mainland China and Hong Kong are taken together as "Chinese". Most of the other countries can be directly associated with one specific ethnic group, except South Africa, Singapore and India. In this study, South African is combined with African, White African and White and Black African; Singapore is added to Chinese and Malaysian; Indian can be aggregated with Anglo Indian and Indian or British Indian; finally, Russian is represented by CIS as a whole since no separate Russian group is provided.

The population distributions of these 20 ethnic groups for the LSOAs in London can be retrieved from the 2011 Census and are illustrated in Figure 5. By distributing the total visitor nights in London by each ethnic group according to Table 5, we have been able to use the spatial distribution of these usual residents by ethnic group to estimate the spatial distribution of guests staying with friends or relatives across LSOAs in London. By summing the tourist nights staying with different ethnic groups in each LSOA, Figure 6(a) visualises the spatial distribution of the inbound guests staying with family or friends. Domestic visitors are equally important as the international tourists in bringing more demand into local residential areas in London. However, for domestic visitors it is difficult to meaningfully allocate these visits in relation to any underlying ethnic indicator. Therefore we have allocated these 13.58m domestic free guests evenly across households in the LSOAs in London, and Figure 6(b) presents the spatial pattern of the domestic guest staying with family or friends.

Having estimated the spatial distribution of guests across London we need now to consider additional household expenditure generated by these visitors. Here we can extract information from the Living Costs and Food Survey (2019). The average weekly household expenditure on "Food and non-alcoholic drinks" in London is £62.40, with the average number of persons per household being 2.6 people. Therefore, on average, expenditure per person on "Food and non-alcoholic drinks" for a week in London can be inferred to be approximately £24. Thus, we assume that the additional household expenditure associated with hosting a guest is £24 per guest per week. Figure 7 shows the spatial distribution of additional household expenditure associated with these visitors. Altogether, we estimate a sum of over £3.7m extra grocery spend per week is induced by hosting guests staying in London, which means the overseas and domestic guests staying with family or friends in London generate almost £193m grocery expenditure per year.

4.4 Day trip visitor

London hosts 319.2 million day trips and receives more than £13.96 billion in expenditure from day visitors. At the aggregate level this is higher than the spend of overnight tourists from both overseas and domestic markets (Table 1). In fact, according to the Greater London Authority (2014), day trip visitors make up 7.33% of London's daytime population, whereas overnight visitors only account for 3.61%. However, the travel behaviour of day visitors is less-well understood, as well as their contributions to the local economy such as expenditures on groceries. The Great Britain Day Visits Survey (2018) reports that day visits to London are dominated by two source regions: London itself (79.0%) and the South East (7.5%). Since these visitors are staying at home overnight, their propensity to purchase groceries to prepare meals (as opposed to snacks or 'food on the go') is limited, and they are unlikely to exhibit a high grocery spend during their visit. Nevertheless, on aggregate, they could generate considerable additional expenditure on incidental purchases due to the large size of this group.

Day trip visitors are defined in line with the daytime population survey (Greater London Authority, 2014) as the 3 Hour + Leisure Day Visitors, whose counts at the borough level are available via the survey. However, day trip visitor statistics in London at the finer spatial scale are unavailable. To help make progress in this respect we harness the percentage of daytime geotweets in each LSOA. Since the day visitors are consisted by a majority of local residents in London as well as day-trippers from outside London, only the geotweets from domestic Twitter users are used at here. The number of day visitors in each borough can be distributed over the LSOAs according to the proportions shown in Figure 8.

According to the Great Britain Day Visits Survey (2018), there is a historical average spend of £44 per 3hr+ visit in London, with purchases involving food in shops or takeaways accounting for 27% of the expenditure (£11.88) of these visits. In line with the suggestion of Newing et al. (2013b), half this expenditure is a good estimation of the amount spent in grocery stores, the remainder attracted to other takeaway food sources. This results in approximately £4.29m spent per week in grocery stores by day trip visitors, which accounts for an additional £223.7m grocery expenditure per annum. The spatial distribution of the estimated day visitor associated grocery expenditure across London is shown in Figure 9.

4.5 Small-area tourist demand layer in London

In this paper we have attempted to build a new demand layer for tourists and visitors in London in relation to a variety of temporary accommodation types: Airbnb, traditional commercial accommodation, guests staying with relatives or friends and day trip visitors who do not stay in overnight accommodation. Table 6 exhibits a summary of the grocery demand from these four tourist groups. The total tourist expenditure in Table 6 is £14.06m. Whilst this is less than both the residential and workplace demand (estimated by the census population data coupled with expenditure rate as £199.8 m and £22.5 m respectively), it contributes a 6.32% increase in the total expenditure in London. What might this mean for individual grocery stores? The Geolytix Retail Points dataset (updated to Jan. 2020) provides individual grocery store locations and aggregated floorspace by LSOA in London (Figure 10). According to the Geolytix database, there are 1,759 grocery stores providing a sum of 14.8m square foot (sqft) of floorspace in

London including 985 convenience stores (with a store size under 3,013 sqft), 647 supermarkets (store size between 3,013 and 30,138 sqft) and 127 hypermarkets (store size over 30,138 sqft). On average, the store revenue from residents and workers in London is £126,379 per week, while tourist adds a further £7,993 revenue to give £134,372 per week, resulting in a £16.0 per sqft per week sale density. This figure is in line with industry reports concerning the sales density of UK's top brands - for example Tesco is £17.11 per sqft in the UK and ROI (Tesco PLC, 2020). Of course, the spatial distribution of tourist activity we have shown above means that this additional expenditure won't be shared evenly among these stores, with some stores likely to attract considerable tourist expenditure whilst others very little. Our subsequent research will seek to allocate these additional tourist expenditures to stores in order to consider the spatial distribution of store level sales uplift.

Figure 11 shows the combined spatial pattern of estimated tourist grocery expenditure at the LSOA level. By comparing this with the grocery expenditure of usual residents in London, Figure 12 presents the uplift of grocery expenditure by LSOA according to the addition of tourist demand. By overlapping with the tourist attractions recommended by VisitLondon (2020) we find that the LSOAs in inner London that are adjacent to major attractions unsurprisingly have substantial uplift. In addition, however, there are other neighbourhoods which have limited tourist attractions but also benefit from tourist demand, such as Heathrow airport, southeast Bromley, northwest Hillingdon and east Enfield. The demand within these areas can be further identified via the examination of demand type. For example, the outer London areas with sizeable uplift are usually due to day trip visits, whereas inner London shows more balanced demand sources from all the four tourist groups.

5. Discussion

In this section we discuss how these results may be of benefit to individual retailers. Adding tourist demand into the estimation of local retail grocery demand first enables the retailers to understand the volume and composition of the customers in each individual store catchment area and tailor the product range to maximise sales opportunities. Any local marketing campaigns might thus be more focused around the accommodation stock in the area. In some areas of London we estimate that 20-30% of all revenue at individual stores may come from tourists, especially those that are likely to be self-catering. The catchment areas of stores in these areas may consider more fresh food which is easy to prepare (especially ready meals, 'food to go' etc). Store management teams might also be encouraged to think about different types of tourist. Mak et al. (2012) provides a good review of how tourists from different countries behave in relation to local food consumption. Some tourists value food products related to their own home countries. Pizam and Sussmann (1995) suggest French, Italian, Chinese and Japanese tourists are more likely to fall into this category for example, whilst Henderson (2016) discusses the importance of providing halal food for visiting Muslim tourists. Thus exploring the country of origin component to the tourist make-up included in our estimates could provide useful additional information for product shelfing. However, there are those tourists that might be searching for more typical UK products to enrich their experiences of new taste sensations. Everett and Aitchison (2008), Kim et al. (2011) and Getz et al. (2014) all discuss the growth of food tourism and show how different demographic groups may be more likely to indulge in the search for local, regional food. Even though this is likely to be more appropriate for restaurants than grocery stores these types of tourists might be inclined to try traditional UK products available in supermarkets. In the future, detecting the demographic groups more inclined to indulge in food tourism in different localities could be aided by the tourist Twitter activity data by person type (cf. Longley et al 2015).

Second, the incorporation of tourist demand within a spatial modelling framework also enables a more informed evidence base to support robust location planning, performance evaluation and impact assessment of local service development and delivery. For example, in relation to existing store performance, actual versus expected or forecasted store revenues might be reviewed in light of the extra demand available from tourists. We also argue that the new demand layer could be used as an input to modelling tools used to support retailers in estimating new store revenues which are so important to consider before a new store is actually constructed (Birkin et al., 2017). Forecasts of future revenues based purely on residential demand may underestimate the potential of a particular location. This may, in turn, mean the financial case for a new store would not stack up and be rejected by senior management. The addition of tourist demand may not simply give better forecasts – it might take estimated revenues beyond the threshold needed to ensure long-term store viability. In subsequent research we hope to show the value of this new demand layer when introduced into typical store location models.

Third, the estimated tourist demand also has the potential to investigate any latent "tourism food deserts" in our study area. In Figure 10, we showed how the distribution of grocery stores is widespread across both inner and outer London regardless of the locations of main tourist attractions, since these stores were predominantly located to serve local residential demand. The distribution of tourist demand plotted against existing stores can reveal a significant mismatch between tourist demand and grocery supply. The gaps, or tourist food deserts, may thus provide retailers with opportunities for (convenience) stores targeted more fully towards tourists. To illustrate this idea we employ some additional spatial analysis here. In Figure 13 we identify the areas that have the great differences between estimated tourist demand and grocery floorspace. The darkest shading in Figure 13 represent areas which have high estimated tourist demand but low grocery retail floorspace. These areas may provide substantial degrees of sales uplift to newly opened stores or increased store floorspace within existing stores.

In undertaking this research we realise that we have made some assumptions that are difficult to validate in the normal way, especially when trying to attach sensible spending patterns to each tourist group. For data which is 'missing', we have tried to use figures routinely used by internal store location teams (obtained via our retail partner links). We understand that a detailed and fine-tuned tourist spending survey conducted at the local area could be beneficial in future work. In the meantime, there are no existing studies which have reported any small-area demand estimates which can be used to validate the accuracy of some of the estimations we have needed. That said, we have shown that even when using cautious spending estimates from the retail industry, the uplift to grocery spend is very significant. However, we hope in the future to be able to work with a leading partner grocery retailer in London to see if these uplifts make sense when we compare sales between stores which are in tourist areas with those that are not. Exploring store revenue performances in this way will go a long way to helping us to produce even more robust sales uplift forecasts in the future.

6. Conclusions

Urban tourism plays an important role in stimulating local economies. Most of the existing research examines the economic impact of tourist shopping via questionnaires to survey the tourist shopping behaviours and expenditures at the macro-level of destinations or associated with specific shopping sites or particular temporary events (Sullivan et al., 2012; Murphy et al., 2011). These studies help shed light on tourist shopping experiences to assist destination management and operation, but contribute little to the understanding of the geographically varied distribution of tourist shopping or the magnitude of these economic drivers at the local, small-area level. The main problem traditionally has been the deficiency of fine-scale population statistics regarding tourists and their behaviours. To overcome this barrier, we have collated data from multiple data sources, for four different types of visitors: overnight tourists staying in Airbnb self-catering accommodation, traditional serviced accommodation, guests staying with relatives or friends and day trip visitors who do not use overnight accommodation. To achieve this task, we have combined conventional data from published industry surveys and statistics with emerging online (big data) sources to estimate small-area tourist numbers in urban areas.

The enriched tourist population dataset shows the key patterns of tourist distributions at a finer spatial and temporal granularity, which can be incorporated with residential and workplace statistics to further understand the diurnal and nocturnal population composition in our Greater London study area.

Whilst our primary focus and interest is on tourists' grocery expenditures, our high spatial and temporal granularity estimates of small area tourist distribution, disaggregated by visitor type, could offer tremendous potential for other retail sectors and for tourism destination management and planning. It highlights a detailed example of the benefits and insights that can be gained by combining big data sources which capture sub-groups of tourists and their spatiotemporal distributions at the sub-destination level. Ye et al. (2020) present a broader suite of examples which demonstrate the type of destination management issues that indicators derived from these data could support. In relation to our specific focus on tourist grocery shopping expenditure, our study reveals that this expenditure is considerable and spatially varied according to the degree of tourist concentration.

Coupling the associated grocery spending of each of the four tourist subgroups with the small-area spatial distribution of tourist populations has allowed us to estimate an additional demand layer to the more traditional residential-based estimates used primarily in store location research. The additional tourist demand surface demonstrates a concentration of grocery expenditure uplift around London's Central Activity Zone with a far more dispersed pattern of tourist demand existing in the neighbourhoods of outer London.

Although we have taken London as our example, the devised methodology used here to produce the new small-area tourist retail demand estimates can also be leveraged to other urban destinations which host significant tourist activity. In addition, although we have focused on the grocery shopping market the approach could be utilised for all other retail segments providing that average expenditure rates are available for the appropriate retail sector. We hope other researchers may take up the challenge to explore other cities and retail sectors.

Appendix

The produced tourist population dataset and the final tourist grocery demand layer are available at https://rpubs.com/ziye/touristdemandestimation.

Declaration of interest

The authors declare that they have no competing interests.

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