Incorporating seasonal visitor demand in retail location modelling

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The candidate confirms that the work submitted is his own, except where work which has formed part of jointly authored publications has been included. The contribution of the candidate and the other authors to this work has been explicitly indicated below. The candidate confirms that appropriate credit has been given within the thesis where reference has been made to the work of others.

Chapters 4 and 5 draw on analysis and findings which have been reported in the following publications:

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The research within each paper has been carried out by the first named author. All three manuscripts have been prepared by the first named author with the input of co-authors being advisory and editorial.

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Abstract

Retail location planning within the grocery sector employs sophisticated modelling to evaluate the trading potential of proposed new stores and investments. Demand side expenditure estimates are commonly used in conjunction with spatial interaction modelling to analyse consumer flows, determine store catchment areas and predict revenue in advance of store construction. Retailers note that these revenue predictions often underestimate demand in tourist areas, where non-residential demand, originating from visitors, can generate considerable seasonal sales uplift at the individual store level. Modelling visitor demand of this nature is an under-researched area and is addressed within this thesis in order to improve the modelling and revenue estimation capabilities of location planning teams, and to enhance understanding of tourism's local economic impact.

This research is carried out with the support of Sainsbury's (as an ESRC CASE award partner) and specifically considers location-based modelling for application in the grocery sector. The thesis draws considerably on stores within Cornwall and Kent, especially those in popular (and highly seasonal) coastal resorts. With rare access to store and consumer loyalty card data, this thesis identifies the impact of visitor expenditure on store-level grocery demand.

Subsequently, a methodology is developed in order to estimate small-area grocery demand in highly seasonal (coastal) tourist resorts, accounting for the spatial and seasonal variations driven by visitor expenditure. These demand estimates are used in conjunction with a Spatial Interaction Model (SIM) (developed and calibrated specifically for this thesis) to estimate store revenue and market shares in tourist areas. This thesis demonstrates that demand side estimates and a spatial modelling approach are able to generate robust revenue predictions for stores in highly seasonal tourist resorts. The discussion clearly highlights the versatility of the model in addressing demand and supply side interventions, and outlines the impact of this form of analysis on store location based decision making in tourist resorts.

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List of Abbreviations

ATD	Average Trip Distance
BH&HPA	British Holiday and Home Parks Association
B&B	Bed and Breakfast
CCC	Camping and Caravanning Club
CRS	Cornwall Retail Study
ELVS	England Leisure Visits Survey
EPOS	Electronic Point of Sale
ESRC	Economic and Social Research Council
GBDVS	Great Britain Day Visitor Survey
GBTS	Great Britain Tourism Survey
GOF	Goodness of Fit
GVA	Gross Value Added
HSE	Health and Safety Executive
IGD	Institute for Grocery Distribution
IHS	Integrated Household Survey
IPS	International Passenger Survey
LCF	Living Costs and Food Survey
LDF	Local Development Framework
LPA	Local Planning Authorities
LSOA	Lower Layer Super Output Area
MSOA	Middle Layer Super Output Area
NPD	National Population Database
NPPF	National Planning Policy Framework
NRS	National Readership Survey
OA	(Census) Output Area
OAC	Output Area Classification

OECD	Organisation for Economic Co-operation and Development
ONS	Office for National Statistics
OS	Ordnance Survey
OSM	Open Street Map
PPS4	Planning Policy Statement Four
RIBOS	ReZolve Internet-Based Occpancy Survey
SIM	Spatial Interaction Model
SRMSE	Standardised Root Mean Square Error
STEAM	Scarborough Tourism Economic Activity Monitor
SusTRIP	Sustainable Tourism Research and Intelligence Partnership
SWRDA	South West Regional Development Agency
SWT	South West Tourism
SWTA	South West Tourism Alliance
TIU	Tourism Intelligence Unit
TSA	Tourism Satellite Account
TSE	Tourism South East
UKTS	United Kingdom Tourism Survey
UNWTO	United Nations World Tourism Organisation
VFR	Visits to Friends and Relatives

Both metric and imperial units are used throughout this thesis in order to conform to established conventions and for consistency with external sources.

Chapter 1: Introduction - aims, objectives, structure, scope and contribution of this thesis

1.1 Research outline and context

The research reported in this thesis represents the outcome of an ESRC collaborative CASE award and seeks to incorporate seasonal visitor demand in location-based modelling for retail location planning. It has been undertaken with support from the 'Location and Network Planning' team (referred to simply as 'Location Planning') at Sainsbury's Supermarkets Ltd. (referred to as Sainsbury's). Sainsbury's are a major UK groceries retailer with a network of over 1,000 stores and a strong presence in food, non-food and online grocery retail. Location planning is an important strategic and operational function across the retail industry and large grocery retailers such as Sainsbury's boast some of the largest location planning functions (Reynolds and Wood, 2010b). Their teams employ sophisticated modelling to carry out network planning and site evaluation. An important role of the location planning function involves predicting the revenue and associated market share of proposed new stores in advance of actual investment (Birkin *et al.*, 2002). The trading potential of proposed new stores influences how much retailers are prepared to pay to secure a site (and construct a new store) and ultimately determines whether there is a sufficient financial business case to justify a proposed investment (Birkin *et al.*, 2010b).

As explored fully in Chapter 2, the spatial interaction model (SIM) (often referred to as the 'gravity model' within industry) has become an important tool for revenue estimation within the grocery sector (Birkin *et al.*, 2010b; Reynolds and Wood, 2010a). A SIM relates consumer demand and retail supply, estimating flows of consumer expenditure between demand origins (typically residential) and competing stores. With increasing volumes of consumer data, sophisticated SIM have been developed to estimate store revenue and trading potential (Birkin *et al.*, 2010a). In many areas of the UK, that revenue is driven by the expenditure originating from residential households. A comprehensive understanding of the composition and characteristics of residential demand (often derived through census data, geodemographics and loyalty card data) means that modelling can generally generate robust revenue predictions (Birkin *et al.*, 2002).

Nonetheless, in areas with large non-residential populations (e.g. a daily commuter inflow, termly inflow of students or a seasonal inflow of tourists), retailers such as Sainsbury's note that their modelling often underestimates available demand (and store revenue). This is particularly true when stores are located in coastal resorts and other highly seasonal tourist areas. Here, modelling often fails to account for store-level revenue uplift during the tourist season, or the spatial and temporal patterns exhibited by this form of demand. This limits retailers' ability to deliver a robust assessment of trading potential, impacting on the strategic

and operational decisions that retailers can make (Feltham and Davis, 2010; Wright, 2011). Retailers thus maximise opportunities to develop their location planning capabilities and associated spatial modelling, in order to make investment decisions with confidence (Birkin *et al.*, 2010b). This thesis seeks to address this weakness, developing a robust methodology to account for seasonal visitor induced demand uplift within location-based modelling.

This thesis seeks to develop both demand side expenditure estimates and a SIM, specifically designed to incorporate visitor demand in the grocery sector. There has previously been very little exploration of seasonal demand estimates for application within store location planning. The provision of store and consumer data by Sainsbury's (including data from the Nectar Loyalty card scheme) also means that this is one of very few examples within the academic literature of an applied SIM that has been developed, calibrated and validated with reference to empirical data supplied by a major retailer.

Modelling visitor demand of this nature is an under-researched area within the academic literature. Surprisingly little is known about the small-area economic impact of visitor expenditure (Buccellato *et al.*, 2010b), yet demand inflow associated with tourism alters demand for goods and services within popular tourist destinations and resorts. The tourist sector is an important driver of consumer demand and associated expenditure in the UK, and the impact of seasonal visitor demand uplift at a store-level can be pronounced (see Chapter 4). It is thus important to understand the impact of seasonal visitor demand on grocery retail services in order to improve the modelling and revenue estimation capabilities of location planning teams, and to enhance understanding of tourism's local economic impact.

The research reported in this thesis has been funded by the Economic and Social Research Council (ESRC) through the Retail Intelligence Building Engagement Network (RIBEN), which seeks to encourage and facilitate collaboration between academics and the retail industry. As part of the collaboration, this thesis has directly benefited from access to valuable industry data sources, particularly store trading data and loyalty card information at the individualised (and anonymised) consumer level. Nonetheless, the focus remains explicitly academic and was not excessively driven by the needs of Sainsbury's, whose input was limited to the choice of study stores and the provision of data, documented within the following Chapters. Informal discussion with key contacts at Sainsbury's has taken place throughout the project, resulting in an output that is of use to their location planning team, alongside considerable interest to the academic community. Section 1.2 outlines the aims and objectives of this research.

1.2 Aims and objectives

This research seeks to develop spatial modelling techniques that can be used (within site location research) to estimate store revenue with accuracy in tourist areas. The overall aims of this research are to:

- Review the existing literature and available industry data to identify the impact of visitor expenditure on store-level grocery demand.
- Develop a methodology to estimate small-area grocery demand in highly seasonal tourist (coastal) resorts, accounting for the spatial and temporal (seasonal) variations driven by visitor expenditure.
- Develop and calibrate a SIM to handle seasonal grocery demand within tourist areas, demonstrating that it can generate robust revenue predictions as a tool for evaluating proposed supply or demand side changes.

In order to meet these aims, the following objectives are addressed throughout this thesis:

- Review the role of spatial interaction modelling as a tool for revenue estimation in contemporary location planning within the grocery sector (Chapter 2).
- Identify the importance of visitors in driving consumer expenditure in tourist resorts, noting the highly seasonal nature of tourist demand and implications for service provision (Chapter 3).
- Ascertain the seasonal nature of trade at grocery stores in major coastal resorts using store-level trading information provided by Sainsbury's (Chapter 4).
- Explore the characteristics of visitor grocery expenditure at the individual consumer level using customer loyalty card data from the Nectar scheme (also in Chapter 4).
- Understand the grocery consumption habits associated with different types of visitor, visit or accommodation, including the induced expenditure associated with hosting visiting friends, relatives or paying guests (Chapter 5, drawing on insight from Chapters 3 and 4).
- Develop a series of seasonal and spatial demand 'layers' at the OA level, incorporating spend by visitors (day and overnight) and local residents (Chapter 5).
- Produce and calibrate a SIM that can be used to estimate grocery store revenue, accounting for seasonal variations in demand (Chapter 6).
- Demonstrate that the SIM, used in conjunction with seasonal demand estimates, can produce robust and accurate revenue predictions and assess the extent to which the SIM can be used for store location planning and supply and demand side 'what if?' analysis (Chapters 7 and 8).
- Comment on the applicability of this approach for use within store location planning and its impact on location-based decision making (Chapter 9).

The objectives are addressed systematically throughout this thesis, the structure of which is outlined in section 1.3.

1.3 Thesis structure and scope

In meeting the objectives outlined in section 1.2, this thesis is organised around the following structure. First, Chapters 2 and 3 situate the study within the established literature. Chapter 2 predominantly draws on literature from the geographic modelling and retail location planning sector and contextualises the study within applied spatial modelling for retail location planning. The discussion situates the research within key supply and demand side changes that have given rise to contemporary location-based decision making and store development opportunities within this sector. This chapter also introduces the theory of spatial interaction and the entropy maximising production-constrained SIM.

Chapter 3 situates the thesis more broadly within the tourist sector, considering the role of visitor expenditure in driving seasonal demand in tourist resorts, outlining the impact of visitor trip purpose and accommodation used (where applicable) on expenditure. Chapter 3 identifies a number of data sources and modelling tools for exploring tourist consumption, but concludes that very little is known about seasonal and spatial patterns of visitor grocery expenditure at the small-area level.

The objectives outlined in section 1.2 are largely met with reference to the county of Cornwall, South West England. Cornwall, introduced fully in Chapter 4, represents a major destination for highly seasonal (domestic) coastal tourism in the UK. Sainsbury's stores in a number of Cornish coastal resorts experience a very pronounced seasonal trade pattern, as outlined in Chapter 4. The Chapter makes use of store and Nectar card data to identify the degree of seasonal sales uplift on a store-by-store basis. The loyalty card data is a valuable tool to identify characteristics of visitors themselves and to identify their consumption habits, drawing contrasts with local residential trade.

Chapter 5 draws on this insight, and a range of census, survey and geodemographic data in order to build a series of small-area expenditure estimates. These demand side estimates explicitly seek to incorporate seasonal expenditure associated with visitors. They include spend by day visitors, all forms of overnight visitor, and induced spend by hosts, alongside small area seasonal and spatial patterns in local residential grocery spend. The Chapter provides a comprehensive overview of the data sources used to identify overall visitor numbers, their seasonal and spatial distribution and associated expenditure.

Chapter 6 incorporates these seasonal and spatial small-area expenditure estimates within a SIM for use in store location planning. The SIM, disaggregated on both the supply and demand side, is developed from scratch and calibrated with reference to Sainsbury's store and loyalty card data. The calibration routine is outlined in full detail with reference to the input data and the operation of individual model parameters. With reference to Sainsbury's stores in Cornwall, Chapter 6 demonstrates that the model, used in conjunction with small-area seasonal demand estimates, can predict store revenue to a very acceptable level of accuracy. Chapter 7 address a number of 'what if?' scenarios that may be considered by

location planning teams. Using the SIM (and examples from Cornwall), a number of store development proposals are evaluated, demonstrating that the model can be used to generate seasonal revenue predictions at the store-level, identifying the impact of new store development on consumer flows, existing store performance and market share.

Chapter 8 produces similar small-area seasonal and spatial demand estimates for an additional study area, East Kent. The nature of tourist demand in East Kent is noted and the Chapter identifies that, as an alternative study area, this area presents a number of challenges and opportunities to further develop the capacity to model visitor demand. With reference to stores in East Kent, Chapter 8 demonstrates that the SIM and demand side expenditure estimates can generate robust revenue predictions. The examples chosen here also highlight the capacity of the model to handle demand side 'what if?' scenarios.

Chapter 9 argues that the demand side estimates and modelling approach could be used with confidence by location planning teams. It suggests that they can generate robust revenue predictions in a range of tourist destinations and for a variety of store types, noting also some of the obstacles that may be encountered when seeking to apply this approach in-house. Chapter 9 also notes the contribution this thesis has made to the academic literature, reflecting one of the only examples of the development and application of a SIM, disaggregated on the demand and supply side and calibrated using empirical store and consumer data from a major retailer's loyalty card scheme.

In meeting the aims and objectives outlined in section 1.2, this thesis approaches the research from the perspective of spatial modelling for store location planning. Such an approach represents the strengths, interests and experience of the author, academic supervisors and research cluster within which this work was hosted. Whilst this thesis draws on literature from the tourist sector (both industry and academic) and has been published within the tourism literature, it does not intend to provide an exhaustive account of the handling of seasonal visitor demand uplift from a tourist sector perspective. It does, however, contribute to a clear gap in the academic literature and seeks to address an issue of interest to industry practitioners, as outlined in section 1.4.

1.4   Thesis contribution and major outputs

This thesis highlights some of the benefits that can be realised through collaboration between academic institutions (in this case with a strong background in location planning) and similar teams within a major retail organisation. This work goes some way to fill an important (and perhaps surprising) gap in the academic literature, that of applications of retail modelling (and specifically spatial interaction modelling), that draw on well-developed and productive collaborations between academia and industry. The opportunity to work on a significant project of considerable benefit, relevance and importance to an external partner gave this research a particularly applied focus, which has been very well-received by the research

community. The research documented within this thesis has been presented at 11 international conferences across a broad range of themes which include regional science, geographic modelling, spatial and quantitative analysis, and also tourism economics.

The research has also been presented at a series of broader events, including a high profile event hosted by ESRC, seeking to bring together academics and key stakeholders within major retail organisations[1]. The event sought to demonstrate the benefits that retailers can obtain through engagement with academia, focussing in particular on collaborations involving consumer data held by consumer facing companies. The interest shown in this work by the ESRC demonstrates that the research reported within this thesis makes use of rarely available industry data, addressing a genuine commercial need and under-researched area within the geographical modelling literature.

Outputs originating from this work have been disseminated via publication, with two publications in print at the time of submission, detailed below:

> Newing, A., Clarke, G. and Clarke, M. 2013a. Identifying seasonal variations in store-level visitor grocery demand. *International Journal of Retail & Distribution Management*, 41(6) p477-492.

> Newing, A., Clarke, G. and Clarke, M. 2013b. Visitor expenditure estimation for grocery store location planning: A case study of Cornwall. *International Review of Retail, Distribution and Consumer Research*, 23(3) p221-244.

These papers, both published within journals that seek to address issues of significance to the retail industry, firmly situate the work within retail location planning. Newing *et al.* (2013a) is based on part of the discussion within Chapter 4 and seeks to illustrate the considerable seasonal sales fluctuations experienced around selected Sainsbury's stores in Cornish coastal resorts. This paper firmly establishes, within the academic literature, the need for store location planning to explicitly address seasonal tourist demand within the revenue estimation process. Newing *et al*. (2013b) begins to addresses the need for small-area seasonal and spatial demand estimates which incorporate expenditure by visitors. The paper draws on material which formed a pilot analysis, subsequently used to inform the expenditure estimation developed in Chapter 5.

A third paper has been accepted for publication:

> Newing, A., Clarke, G. and Clarke, M. 2014. Exploring small area demand for grocery retailers in tourist areas. *Tourism Economics*, Accepted and in press for publication Feb 2014.

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[1] 'Demonstrating the potential for collaboration - modelling seasonal demand for applications within retail store location planning'. Invited presentation at the ESRC Retail Breakfast Meeting, Royal Society, London, 2nd August 2013.

Forthcoming in 'Tourism Economics', Newing *et al.* (2014) demonstrates that seasonal demand uplift (as experienced in grocery stores within Cornish tourist resorts) is driven by visitors. It draws a series of comparisons between the nature of visitor demand and local residential demand and contextualises this research from a demand side perspective, appealing to a far wider audience than the retail community. The insights are documented more fully within Chapter 4 and, with access to loyalty card data from the Nectar scheme, provide a unique insight into the nature of tourist consumption rarely seen in the tourism literature.

Writing in 2010, Birkin *et al.* (2010a) assert that there remains a lack of papers within the academic modelling literature that consider issues encountered when seeking to apply spatial location-based models in commercial contexts (where the needs of clients and the limitations inherent in their data need to be taken into account). Two further papers originating from this thesis are proposed, and it is hoped that these will go some way to address the gap identified by Birkin *et al.* (2010a). With the geographic modelling community as the intended audience, a paper is under preparation (at the time of thesis submission) which draws on the SIM development and calibration, as reported fully in Chapter 6. The proposed paper seeks to demonstrate a clear and practical example of a disaggregate SIM, developed and calibrated in an applied context using empirical data from a major retailer. A following paper, intended for a broader readership (not limited to the modelling community) is proposed which would seek to demonstrate the value of such a model in generating robust store-revenue predictions in tourist areas, drawing upon the range of scenarios presented in Chapters 7 and 8. Such papers would build on a series of review articles (Birkin *et al.*, 2010a; Birkin *et al.*, 2010b) which highlight many of the considerable insights and model developments (in an applied context) that have resulted from applied work with retail organisations.

This thesis and its associated publications (accepted, in-press, in-preparation and proposed) provides a clear example which outlines, in a practical sense, specific issues faced when developing and applying a SIM. Throughout this thesis, the specific issue is contextualised and evidenced using industry data. The development of the model itself, its demand, supply side, interaction data and subsequent calibration routine are outlined in full detail. The thesis clearly evaluates the model performance, demonstrates the type of location-based decision making it can address and considers the contexts in which it can be applied.

Chapter 2 provides a further introduction to the grocery sector and to the modelling approach addressed within this thesis.

Chapter 2: The UK grocery sector – supply, demand and location-based decision making

2.1   Introduction and outline

Chapter 1 outlined the context of this thesis, identifying that it represents an applied research project to incorporate seasonal tourist demand within the location-based decision making and associated spatial modelling carried out by grocery retailers. This chapter introduces the grocery sector, identifying key supply and demand side characteristics and contemporary growth in this sector. This chapter seeks to firmly embed the thesis within applied spatial modelling for retail location planning, considering both the academic literature and established industry practice. The latter may not be fully documented within the academic literature, but, drawing on their extensive industry experience and discussions with industry practitioners, Clarke and Clarke (1995) assert that this form of insight is 'no less valid' than research documented in the academic literature.

This chapter first outlines the overall structure, nature and importance of the UK grocery retail sector. Section 2.2 outlines key planning policies (section 2.2.1), retailer growth strategies and consumer behaviours (sections 2.2.2 and 2.2.3) that give rise to contemporary location-based decision making and store development opportunities within this sector. The role of customer loyalty schemes in maintaining growth and generating consumer insights is also considered (Section 2.2.4). Section 2.3 situates the research within the context of contemporary retail location planning and specifically considers spatial modelling for demand estimation and site assessment. Section 2.4 considers the use of spatial interaction modelling (SIM) to estimate store revenue prior to new store investments. It is this type of spatial modelling that forms the basis of the location-based modelling carried out in Chapters 6-8, addressing a demand side weaknesses in the handling of non-residential tourist demand. Section 2.5 briefly outlines the role of tourist demand in driving store-level grocery demand, setting the context for Chapter 3, which considers the tourist sector as a driver of localised, seasonal demand, in more detail.

2.2   The UK grocery retail sector

Grocery retailers stock food and drink for consumption off the premises, alongside household goods such as cleaning products, pet supplies and kitchen items (Competition Commission, 2008). Groceries is one of the most important and successful retail sectors in the UK economy (Burt *et al.*, 2010; Portas, 2011), worth £169.7bn in 2013 (IGD, 2013). Households spend almost 55p in every £1 of retail spend on groceries and related household items (IGD, 2013), and food spend was one of very few sectors that continued to grow as recession hit in the late 2000s (Saunders, 2011). UK grocers enjoyed a 14.6% share of total

non-food sales in 2010 (Teale, 2011) and continue to expand into this area, yet the sale of food and drink remains their core business. The Institute of Grocery Distribution (IGD) predicts that consumers will spend over £205.9bn per year on groceries by 2018 (IGD, 2013), representing an annual growth rate of almost 4% for a sector which continues to develop new stores and formats to meet the needs of consumers. The IGD (2009b) note that groceries are commonly sold through four 'channels':

> 1) Traditional retail: Sales area less than 3,000 Sq Ft and commonly only stocking a limited range of grocery categories (such as a newsagent or off-licence).

> 2) Convenience (c-store): A store with a sales area under 3,000 Sq Ft, with long opening hours and products from a number of different groceries categories such as fresh, chilled and frozen goods.

> 3) Supermarket (3,000 Sq Ft -25,000 Sq Ft), superstore (25,000 Sq Ft - 60,000 Sq Ft) or hypermarket (over 60,000 Sq Ft): Stocking a full range of groceries, plus non-food products and in-store services (e.g. café). Collectively these store types will be referred to as 'supermarkets' throughout this thesis.

> 4) Online: Through a traditional retailers' online channel or online grocers such as Ocado, who do not have a physical store presence.

Convenience stores and traditional retailers (such as newsagents) make up the bulk of the stores in the sector. However, the market is dominated by less than 8,000 stores that represent supermarkets, accounting for 69.8% of the grocery retail sectors' total value (IGD, 2013), and which are predominantly operated by Tesco, Sainsbury's, ASDA and Morrisons who, along with the Co-Op, collectively account for almost 60% of the floorspace in the sector and 80% of the UK market (by share of consumer expenditure) (Hughes *et al.*, 2009). In no small part, the dominance of these retailers has been driven by the strong focus on consumer insight, innovation and location planning which has fuelled expansion into an array of store formats and locations in order to meet consumer demand. Sections 2.2.1 to 2.2.3 outline key planning policies, consumer behaviours and supply side changes that give rise to contemporary location-based decision making and store development opportunities within this sector.

2.2.1 Growth, the store wars and retail planning policy

The grocery sector is dominated by a small number of major retailers. Their traditional growth has been through the development of large-format supermarkets. Many of these stores were developed in out-of-town locations in the 1980s and 1990s, during a period termed the 'store wars' era (Wrigley, 1991; Wrigley, 1994). Consumer preferences towards 'one stop shopping' and growth in car ownership went hand-in-hand with new large-format foodstore development (Guy, 1996a). Supermarkets offered a greater range of products at more competitive prices than many of their high street rivals and were able to operate stores

more efficiently by reducing staff costs, by developing efficient distribution systems and by exerting pressure on suppliers to reduce costs (Wrigley, 1998). By 1990, there were over 700 superstores in out-of-centre locations (Owen, 2003; cited in Hughes *et al.*, 2009), representing over 15m Sq Ft of retail space (Wrigley, 1998). As a consequence of this rapid growth in store portfolios, market share and profits, Wrigley (1991, p1537) terms the period up to the early 1990s "the 'golden age' of British grocery retailing".

It was during this era of expansion and growth that location planning became firmly embedded in the practices of these retailers, since it was through network expansion that profits could be generated (Clarke and Clarke, 1995). Penny and Broom (1988) note that this rapid building programme was fuelled by the knowledge that there were a limited number of suitable sites available for new superstore development. As a result, retailers used highly competitive and aggressive policies to secure new sites for large out-of-town supermarket development. Guy (1996a, p1575) asserts that the 'store-wars' era reflected "one of the largest construction programmes ever to have taken place in Britain". Fears over lack of competition and market saturation (Guy, 1994; 1996b) coupled with tighter planning restrictions and competition from low cost rivals (known as European limited-line discounters) such as Aldi, Lidl and Netto (now part of ASDA), slowed down the rate of new supermarket development during the 1990s. Nonetheless, organic growth through new store development has remained important within the sector.

This period of rapid growth was marked by concern over the increased dominance of major retailers in the grocery sector. Mergers, take-overs and acquisitions attracted the attention of the Competition Commission, with both Tesco and Sainsbury's achieving regional monopolies in parts of the UK (Competition Commission, 2000). Concerns were also raised that the growth of large-format out-of-town stores were having a detrimental impact on existing retail centres. Early evidence (e.g. Clarke, 2000) has been backed by recent high profile publications (NEF, 2002; NEF, 2005; NEF, 2010) including the Portas Review (Portas, 2011) in which the loss of many independent high street stores and the general decline in the vitality of town and city centres were noted. Since the 1990s, national planning guidance in England has become concerned by the notion that retail development in out-of-town locations will have adverse economic and social effects on town centres and the communities which they serve (Guy, 2007). Shifts in consumer expenditure away from these locations to out-of-town retailers, including supermarkets, have been widely cited as a major cause for this decline (e.g. see Simms, 2006), and subsequent impacts on consumer choice and access to foodstores, particularly among consumers without access to a car (Kirkup *et al.*, 2004).

Planning policy throughout the late 1990s and 2000s reflected this concern for town-centre vitality. New retail store developments are subject to a complex set of planning processes and associated legislation before being approved for construction. In England the planning framework is hierarchical, with national, regional and local policies against which all

proposed developments are assessed. Local planning authorities (LPAs) set out their vision for development in their local area in the Local Development Framework (LDF). At the time of writing, the main form of national planning guidance regarding retail developments currently used by LPAs (in producing their LDF) is the National Planning Policy Framework (NPPF) (Communities and Local Government, 2012), which superseded Planning Policy Statement 4 (PPS4) "Planning for Sustainable Economic Growth" (Communties and Local Government, 2009). One of the key aims of the NPPF is to facilitate economic growth by promoting the vitality and viability of town centres through focussed retail development and service provision. The NPPF maintains the sequential test, introduced in 1996, which seeks to direct new retail uses to town centres first, wherever suitable sites are available. The sequential test outlines that retailers must be flexible in their store formats and approach in order to adapt their business to suit the full range of town centre sites available.

It is undoubtedly a result of these planning restrictions, coupled with the changing characteristics of demand, that have influenced new store development and location-based decision making in the first decade of the 21st century, explored in the following sections.

2.2.2   Changing supply and demand in the grocery sector

Retailers have become increasingly flexible and innovative to fit their new store developments within stringent planning policy, demonstrating customer focused-innovation and maintaining growth in the face of tightening regulation (Wood *et al.*, 2006; Wood *et al.*, 2010). Retailers have, for example, compromised on their usual supermarket store designs in order to develop supermarkets which are suitable for within-centre or edge-of-centre locations (which are not subject to such stringent planning policy), allowing continued development of large-format stores (see section 2.2.3). Major grocery retailers have used their established brands, product ranges and in-store customer service, coupled with their economies of scale and operating efficiencies to enter the convenience market. Here they have undoubtedly raised standards and consumer expectations in a traditionally fragmented sector, characterised by high prices, limited ranges and poor service (Wood *et al.*, 2006). This may represent a direct response to planning policy, but also reflects rapidly changing consumer preferences, with consumers increasingly shopping for groceries more frequently, visiting smaller convenience stores to 'top-up' or supplement their main household weekly shopping trip. Over 50% of consumers are reported to visit a convenience store at least once a week, with many consumers not planning meals or purchasing fresh food beyond the next few meals (Competition Commission, 2007; Freedman, 2010). Consumers thus increasingly demand quality and affordable fresh food that is available close to home or work (Wood *et al.*, 2010).

Major retailers have created smaller and differentiated store formats (often via a sub-brand such as 'M&S Simply Food' or 'Tesco Express') suited to the needs of the convenience market and to specific locations, such as transport hubs, city-centres, suburban

neighbourhoods or petrol station forecourts. Stores in transport hubs and city-centres may provide consumers with additional convenience and flexibility, tapping into consumer demand that may not be met effectively by traditional supermarkets. Stores in suburban neighbourhoods may be highly accessible to the growing elderly population (with the over 65 age group expected to grow by over 40% by 2031 (GVA Grimley, 2010)), whilst the growth of single person households (at a rate that exceeds population growth), is also driving additional household level demand for groceries in certain areas, with these consumers often seeking convenience (IGD, 2009a; Boitoult, 2008; Langston *et al.*, 1997). To this end, Tesco claim that they now boast a " flexible range of formats" which enable them to "adapt [their] approach to local customers – wherever they are – from 'Extra' hypermarkets to 'Express' convenience stores" (Tesco, 2010b, p5).

Major grocery retailers have also been able to use their size, scale, capital and established brand names to dominate online grocery retail which accounted for £4.8bn of consumer spend in 2010 (IGD, 2010). In the period 2003-2010, 46.8% of total retail growth went to online channels (Saunders, 2011), and online groceries are anticipated to be worth almost £10bn per year by 2015 (IGD, 2011). Online grocery retail is generally supported by a physical store presence for picking, packing and despatching orders. The exception would be Ocado (online only) and some warehouses or 'dark stores' that are used to service online grocery orders. Physical store presence and location remain fundamentally important in servicing orders for the online channels (Burt *et al.*, 2010), with evidence presented from an IGD survey of consumers suggesting that reliable delivery is the most important factor in determining their online store choice (IGD, 2011, p1).

Whilst much growth is taking place within the convenience and online markets, large-format stores remain an important part of grocery retailers' existing estates and expansion plans, as outlined in section 2.2.3. The introduction of small-format stores has represented a challenge for store-location planning, with location planners having to adapt their well-established revenue forecasting methods and tools for application to their retailers' convenience estate. Given the nature of the collaboration and the modelling approaches used, these stores do not form the basis for this thesis, yet have been included in this discussion in order to contextualise the work within contemporary growth within the grocery sector. Section 2.2.3 considers the continual importance of large-format stores within retailers' growth strategies. These stores (and the location planning techniques applied to manage the large-format store portfolio) represent the focus of the modelling presented within this thesis.

2.2.3 The importance of large-format stores within UK grocers store portfolios and expansion plans

Difficulties in obtaining planning permission coupled with a lack of suitable sites and potential market saturation does, inevitably, make it increasingly difficult to construct new large-format stores. Mergers and take-overs have thus become an important part of the

growth strategy for some grocers, allowing them to strengthen their position in certain geographic regions (e.g. Morrisons takeover of Safeway in 2003), acquire new store formats (ASDA takeover of Netto in 2010), or to increase their scale within the market (e.g. Co-Op purchase of Somerfield in 2009). Yet, in spite of tightening planning restrictions (which Guy and Bennison (2002) cited as a 'virtual ban on superstore development') and legislation relating to competition in the grocery sector, the UK government claims that its policies support supermarket development (e.g. see Field, 2010; Skidmore, 2010). Policy (and lobbying from major retailers) recognise that continued growth in large-format stores is providing much needed economic growth, jobs and regeneration (Guy and Bennison, 2007). A body of evidence suggests that new supermarket developments, especially when well-connected to existing centres, can create a vibrant shopping centre, maintaining the vitality and viability of existing centres. This is especially true within many smaller market towns where both supermarket and corporate c-store development has been seen to enhance town centre attractiveness as a shopping destination. Here, these may act as an anchor store, increasing town-centre footfall and retaining expenditure locally (Hastings, 2011; Wrigley *et al.*, 2012; Wrigley and Dolega, 2011; Wrigley *et al.*, 2009; Wrigley *et al.*, 2010).

Whilst some of this growth has been in smaller-format stores, the on-going development of larger stores remains fundamentally important to all the major grocery retailers, and will continue to account for a considerable proportion of the floorspace growth in this sector. Burt et al. (2010, p177) go so far as to assert that retailers, with relation to planning policy, "have not really felt too constrained and new formats and developments have occurred in many towns and cities". Simms (2006, p91) suggests that "Tesco's real plan is to achieve still further huge growth by expanding its large supermarkets into massive hypermarkets", with all stores having being designed and built to be able to accommodate large extensions. In seeking to construct large-format stores, both Tesco and ASDA have also become urban regeneration partners, opening some of their largest stores in deprived communities. Often stores are developed in partnership with local authorities and offer jobs and training to local unemployed people in return for some relaxation of planning policy (Guy and Bennison, 2007; Wood *et al.*, 2010; Elms *et al.*, 2010). By contrast, Wood *et al.* (2010) note that Sainsbury's have never pursued a strategy to open stores as part of urban regeneration schemes (with one exception) as its higher-end brand has limited ability to perform well in lower income areas.

Thus, whilst much of the literature has recently highlighted the growth of smaller format stores (e.g. see Shukri, 2010; Wood and Browne, 2007), discounters (e.g. see Aggarwal, 2003; Thompson *et al.*, 2012) and online grocery shopping, all the major retailers remain committed to opening larger supermarkets, with these stores offering economies of scale for the retailer. These large-format stores are also far cheaper to construct, and so retailers maintain pressure on the government and LPAs for out-of-centre sites (GVA Grimley, 2011). Where sites suitable for retailers' preferred 'warehouse style' stores have not been

available (or have been restricted by planning permission), retailers have demonstrated flexibility in terms of format, compromising on the provision of parking, developing stores split across multiple levels or as part of mixed-use schemes (including housing or office space) in order to gain planning permission (see Guy and Bennison (2007) for a full range of flexible approaches from the retailers' perspective). In September 2010, Sainsbury's opened its largest superstore in England (Crayford; over 100,000 Sq Ft), Scotland (Darnley; 90,000 Sq Ft) and Wales (Newport; 76,000 Sq Ft) (Sainsbury's, 2011b), providing evidence that growth via large-format stores is still possible and actively pursued by retailers.

Within these larger stores, growth has taken place in the non-food departments. In a typical ASDA large-format store, higher margin non-food goods (including clothes and electrical goods) account for up to 50% of the floorspace (GVA Grimley, 2010). Sainsbury's note that they aim to devote half of all new sales space to non-food items (IGD, 2009c) suggesting that even larger new stores will need to be built in order to accommodate increasing non-food ranges alongside their existing food offer. Grocery retailers have also developed specific non-food stores in both town centre and out-of-town retail park locations including ASDA 'George' (clothing), ASDA 'Living' (household goods) and Tesco 'Homeplus' (household goods). Since these new stores commonly incorporate services such as post-offices, GP surgeries, dentists and opticians (which would previously have been located on traditional high streets), the location of these large-format stores remain important in delivering a whole range of local services.

In spite of a shift to more frequent convenience shopping, recent studies (Clarke *et al.*, 2012; Kirkup *et al.*, 2004) noted that residents value having a large store nearby, no doubt driven by the increased choice and product ranges, spacious and more attractive shopping environment and often lower prices. To this end, Elms *et al.* (2010, p825) assert that they "find it difficult to anticipate much deviation from a car-borne, superstore-based shopping future for the masses". Developing large-format stores thus forms an important component of the spatial modelling carried out by location planning teams working within the major grocery retailers. It is this form of store development which draws upon established location-based spatial modelling that is the focus of this thesis. Section 2.2.4 considers broader changes in the relationship between supply and demand following the introduction of consumer loyalty cards, before considering store development further (in the context of location planning) in section 2.3.

2.2.4 Consumer loyalty and consumer insights as a driver of growth

Sections 2.2.1 - 2.2.3 noted that strong consumer demand, coupled with continual investment and innovation by the major grocery retailers, has fuelled new store development and diversification into new sectors (e.g. online), formats (convenience) and locations (e.g. transport hubs) to maintain market share in a competitive environment. The grocery sector is highly competitive and consumers have a choice of a range of retailers, store formats and

channels through which to purchase groceries. Whilst the importance of new store development (organic growth) has been highlighted, grocery retailers have also sought to grow their share of the market (and of consumer expenditure) through intense competition, diversification into other product and service sectors (e.g. banking and insurance) and through deeply embedded practices to maintain customer loyalty. In no small part, contemporary growth in the grocery sector has been fuelled by the introduction of customer loyalty schemes, as outlined within this section.

Tesco was the first grocery retailer to introduce a loyalty card, launching its Clubcard scheme in 1995, with around 13m active members (Burt *et al.*, 2010). Alongside similar schemes within the grocery sector (such as Sainsbury's Nectar card) or in other sectors (e.g. Boots Advantage Card with around 15m members), card holders are rewarded for their purchases, receiving quarterly money-off vouchers based on points collected on all transactions. Customers are thus rewarded for their loyalty and these schemes attract consumer spending away from competitors, help maintain market share and operate as very effective marketing tools, allowing retailers to communicate with consumers via individualised postal statements.

The real value of schemes such as Clubcard and Nectar is, however, the consumer insight that can be gained from analysing the data collected each time a loyalty card is used in-store. Major food retailers such as Tesco have been able to use loyalty card data to deliver customer insight and build relationships with customers (Wood *et al.*, 2010). The Clubcard scheme has, for example, been credited as a tool which changed the way Tesco made decisions, offering insight that drove overall strategy, store management and product development with Humby *et al.* (2008), p5 claiming that "through Clubcard, Tesco has defied many of the principles of conventional food retailing that dominated the last 50 years of the 20th century".

Grocery retailers traditionally have little information on their customers. Groceries are not bought on account, nor are consumers personal details routinely collected at the point of purchase. As such, a loyalty scheme is a very powerful tool for collecting customer data, particularly given the high number of transactions and frequency of visit among many customers. The value of the customer insight that can be gained from loyalty cards is so great that, in 2001, Tesco bought a majority share in Dunnhumby, the data analysis company that translated Clubcard data into customer insight. In the case of Tesco, customer insight from the Clubcard scheme allowed them to segment customers, initially by age, and more recently by lifestyle, (based on products purchased) and understand more about their consumption habits.

Humby *et al*. (2008) explain that Tesco had previously used census data and conventional geodemographic insights for a similar purpose but realised that loyalty card data provided a unique individualised insight based on actual purchasing decisions, rather than inferred

behaviour linked to aggregate geodemographic indicators. This insight initially revealed simple characteristics about consumer behaviour, such as which department consumers shop in, how frequently they visit the store, how much they spend and how far they have travelled (Humby *et al.*, 2008).

By 1997, Humby *et al.* (2008) note that Tesco had created a 'customer insight unit', designed to make full use of loyalty card data across the business. The unit combined the statistical skills of their site location team with the commercial and marketing teams, and, with new computing power to fully analyse the large volumes of data, Clubcard became far more than a marketing or promotional tool. Customer insight from the Clubcard scheme is used for site selection, identifying customer trends, building better promotions and for developing in-store ranging. Insight is also used for driving footfall, managing in-store availability, developing and evaluating the success of new-formats and responding to competitor store openings (Humby *et al.*, 2008). Loyalty card data of this nature has also been demonstrated to be an important tool for grocery retailers expanding into new sectors (such as financial services) and evaluating the success of mailshots and other forms of direct marketing (Berry and Longley, 2005).

This thesis relies on extensive consumer insight drawn from the Nectar scheme, for which Sainsbury's were a founding member. The multi-retailer scheme, launched in 2002, includes Debenhams and Barclaycard (who have both subsequently withdrawn from the scheme), Ford, Expedia, The AA (Automobile Association), Homebase, British Gas and in excess of 500 online partners, including Amazon. The range of retailers, organisations and sectors means that the scheme has built up a wealth of personal data on individual and household consumption. Over 50% of UK households have an active Nectar card, representing around 18m Nectar cards (Nectar, 2011). Nectar claim that it is possible to earn points on 49% of overall household expenditure, thus Nectar card data is a comprehensive source of non-surveyed information on household consumption.

Sainsbury's are one of the schemes most popular members, with around 12m active cards used at Sainsbury's stores, although the participation rate varies by store and by type of consumer. No loyalty scheme could, however, claim to achieve 100% coverage of consumers. Humby *et al*. (2008) report that only 60-75% of consumers at any store use Tesco's Clubcard, and certain groups (such as students) tend to show low uptake of and little responsiveness to loyalty schemes. Nonetheless, when combined with electronic point of sale data (EPOS) from till systems (which record products purchased during each transaction), loyalty schemes have become an important approach to understand customers via data collection and subsequent customer insight. Humby (2010) asserts that loyalty schemes will continue to grow, with the prevalence of smart phones likely to replace cards themselves and encourage uptake among previously under-represented groups.

The Nectar scheme is a powerful source of consumer data, used to develop customer insight and for model calibration in this thesis. As well as being a tool to derive customer loyalty, loyalty cards have driven a data-led expansion of customer insight among grocery retailers which has informed all aspects of the business, especially location planning, as explored fully in section 2.3.

2.3   Location Planning within the UK grocery sector

Location-based decision making undoubtedly represents one of the most important functions within any retailer. It is through their network of stores that retailers traditionally interact with customers. In the highly competitive grocery sector, one of the key 'battlegrounds' during the 'store-wars' era involved the rapid acquisition of sites suitable for new store development and construction of new floorspace. Whilst the nature of the store building programmes have changed, it was the 'store-wars' era that drove the development of site location teams within major grocery retailers and embedded within them a highly competitive nature towards new store development. All the major UK grocery chains have specialised teams of in-house location analysts, who carry out sophisticated spatial analysis to identify new sites, estimate market areas associated with new and existing stores and forecast revenue in advance of new store investment (Birkin *et al.*, 2002). Reynolds and Wood (2010b) note that grocery retailers tend to carry out the most sophisticated site location research and are more likely to have their own specialised in-house teams than retailers in any other sector, managing some of the largest store portfolios. These retailers also benefit from some of the most powerful consumer insights driven by loyalty schemes, EPOS (Electronic Point of Sale) data and geodemographics (Birkin and Clarke, 2009).

A recent survey of location planning teams identified their primary role being to support the financial business case for new stores (Reynolds and Wood, 2010a). An important component of their work thus involves an assessment of the trading potential of a proposed site and the prediction of store revenue in advance of investment. Whilst Tesco and Sainsbury's have the largest, longest-established and most sophisticated in-house teams, other grocery retailers have recently introduced specific location planning teams. For example, the location planning team at Morrisons was only formed in 2009 and sought to bring a consistent, data driven and customer focussed approach to location-based decision making (Brodley, 2013). Whilst potential new store investments had previously been assessed by the Morrisons property department, the location planning team was able to take a more strategic approach, developing a network plan, 'wish list' of new stores and a strategy for expansion of existing stores (Brodley, 2013). Increasingly therefore, the work of location-planning teams involves broader analysis of the performance of entire store networks, termed 'network planning' and this includes assessing the impact of proposed or potential store acquisitions and competitor activity (see for example Poole *et al.* (2003) and Reynolds and Wood (2010a)).

Site location teams are thus fundamental to many areas of a retailers' operations and operate at a strategic level (e.g. evaluating sites and generating revenue predictions in advance of major investment decisions) and at an operational level (e.g. assisting marketing teams with store based demographic information or monitoring store performance against forecast revenue predictions in day-to-day operations). It remains, however, the search for new sites (or sites suitable for relocation of existing stores) that forms the bulk of work for location planning teams, according to a recent survey of location planning functions across retailers (Reynolds and Wood, 2010b).

Whilst the preceding discussion has highlighted that convenience stores are part of major grocery retailers' growth strategies, the following sections (in common with the remainder of this thesis) consider specifically location planning and spatial modelling as applied to supermarket (stores over 3,000 Sq Ft) networks. This focus results from the nature of the collaboration giving rise to this thesis, which specifically seeks to address the modelling employed by the team responsible for supermarket location planning within Sainsbury's. Sainsbury's split its location planning team in the early 2010s, introducing separate teams to handle its supermarket and convenience estate, recognising that very different approaches were required for network planning. Gell and Mulcahy (2013) (Sainsbury's) and Brodley (2013) (Morrisons) note that convenience store revenue forecasting commonly employs different location modelling and revenue estimation tools. Convenience store forecasting is based far more on the immediate catchment area around a store, utilising simple buffer and market share analysis as opposed to the well-developed suite of spatial models applied to their supermarket estates.

This thesis does not seek to comment on, or outline, the full range of approaches used for site location analysis across all formats, but is instead focussed almost exclusively on spatial interaction modelling as applied to large-format store revenue assessment. It is a demand side weakness in the handling of visitor demand within this model that is of interest and relevance to the modelling employed herein. For a comprehensive overview of the full suite of approaches used for location planning, store revenue estimation and market share analysis, see Reynolds and Wood (2010b) and Birkin *et al.* (2002). Section 2.3.1 briefly outlines the growth, development and role of location planning teams within major retailers, linking theory and practice.

2.3.1 Growth and nature of location planning within UK grocery retailers

In the 1960s, Sainsbury's formed its 'Site Potential Statistics' department (which went on to become the present day 'Location Planning' team). Initially the insights this team could generate were simplistic, drawing largely on analogues and checklist-style comparisons with existing stores to assess the trading potential of new sites (Wright, 2008). Such an approach makes assumptions about new store performance based on the observed performance of

existing stores with similar characteristics. The 1970s and 1980s represented a significant milestone in the development of sophisticated location planning, replacing traditional concepts (such as Christaller's Central Place Theory) with more sophisticated analysis and modelling. Data and modelling tools were increasingly available and a series of articles published in the mid-1980s clearly highlight the key network-based concerns that location planning had begun to address. For example, Bowlby *et al*. (1984; 1985a; 1985b) considered in turn: the 'search' for new areas for store investment; techniques to predict new store turnover, and approaches to evaluate the trading performance of existing stores. At this time, revenue predictions utilised regression analysis across a broad set of variables (which can be compared across stores), such as total sales area, catchment demographics and the degree of competition (see Birkin *et al.* (1996) for more detail on the use of analogues and regression analysis for store revenue estimation). Across the industry, such approaches were often supplemented with an intuitive approach based on the 'gut feel' of senior managers and executives (Penny and Broom, 1988), often based on very limited knowledge and insight.

Wright (2008) identifies that during the 1980s, census data became available in electronic form and the introduction of GIS and desktop PCs allowed the Sainsbury's location planning team to develop a computerised spatial forecasting model to estimate store revenue. This model incorporated simple drive time and market-share analysis (in conjunction with existing analogues) to assess potential store revenue (Wright, 2008). At the time, Wrigley (1988, p30) asserted that "never before have the skills of locational analysts, developed and practised by geographers and planners been so closely identified with the commercial imperatives of retailers". The first use of more complex 'gravity models' (introduced in section 2.4) was by Tesco in 1981 (Guy, 1994), followed by Sainsbury's in the late 1980s. Concerns among the Sainsbury's team that their early gravity model was insensitive to important considerations such as store access and competitor strength (which were important influences on their store performance) meant that its impact on decision making was limited. The analogue approach remained the primary revenue forecasting tool at Sainsbury's during the 1990s (Wright, 2008), which represented standard practice across the industry at this time. Even in 2010, a survey by Reynolds and Wood (2010b) suggests that many retailers still place huge importance on the insight gained from analogous approaches. These approaches do, however, often fail to account for the complexity of consumer flows, which more sophisticated spatial modelling approaches are able to handle.

During the mid-1990s, many retailers began making use of proprietary GI systems to supplement the insight gained from analogies. Retailers were able to carry out analysis and visualisation, utilising the wealth of spatially referenced data that they began to have at their disposal following the introduction of loyalty cards and the widespread availability of census and geodemographic data, allowing location analysis to grow in sophistication (Horner, 2009). GIS provided retailers with tools to undertake drive time analysis, allowing them to identify the size and characteristics of the population that live within thresholds of individual

stores. Coupled with knowledge of competitor presence, store catchment population characteristics can be used to predict sales and revenue. Wright (2008) for example outlines that in the late 1990s, this approach, utilising data from Sainsbury's newly introduced 'reward' card (later replaced by Nectar) and geodemographic classifications, allowed them to understand more about their customers spatial origins and estimate market shares within store catchment areas more accurately. This approach begins to acknowledge that an understanding of consumer flows is important in determining and forecasting store revenue, leading to the introduction of a more sophisticated gravity model (or SIM) within Sainsbury's location planning team (see section 2.4).

Whilst early approaches to incorporate spatial modelling within store location planning may not have been able to match the accuracy of existing analogue approaches, they were informed by academic theory, drawing on some of the quantitative and analytical approaches at the time (Davies and Rogers, 1984). It was this link between academia and the grocery industry that played an important role in developing early 'gravity models' into the spatial interaction models that are widely applied today (Birkin *et al.*, 2010a; Roy and Thill, 2004), with many of these retailers later developing the capacity to build these models in-house (Birkin *et al.*, 2010a; Reynolds and Wood, 2010a). It was undoubtedly work carried out by Sir Alan Wilson, Mark Birkin, Graham Clarke, Martin Clarke and their colleagues and clients at GMAP in the 1990s that has fully embedded the link between academia and industry practice in the development and application of spatial models for location-based decision making in the retail sector. GMAP Ltd., a commercial spin-off from the University of Leeds, developed these models from their theoretical components into models that work in practice within a variety of commercial organisations.

Organisations such as GMAP were well-placed to develop increased sophistication in location-based modelling as new tools (e.g. GIS), demographic and customer data and graduates with GIS and data analysis skills became available (Birkin *et al.*, 2010a; Jones and Hernandez, 2004). The work of Birkin, Clarke, Clarke and Wilson has informed the formulation of the seemingly straightforward model parameters of supply, demand and interaction, based on what they term 'major research and development' to apply the models in specific business contexts (Birkin *et al.*, 2010a). As a result, spatial modelling has become a widely used tool across the sector, with Sainsbury's re-introducing a SIM, called the 'Grocery Store Potential Model' in the 1990s. It is a demand-side weakness identified within the 'Grocery Store Potential Model' that this thesis explicitly seeks to address and section 2.4 first introduces the concept of SIM (as applied to retail location planning), before considering the identified demand side weakness in handling seasonal visitor demand.

2.4 Spatial interaction modelling as applied to store location planning in the grocery sector

SIM has become an important tool for analysing, explaining and predicting flows over space within geography, transport planning and regional science (Birkin *et al.*, 2010a). Varied applications include modelling of commuter flows (Lloyd *et al.*, 2007), education provision (Harland, 2008), migration (Dennett, 2010) and, importantly, location theory. In retail location planning, SIM are widely used to estimate flows of consumer expenditure from origin (demand) zones to one of many accessible competing stores or retail centres. Origin zones are usually thought of as neighbourhoods (representing residential locations), and flows are driven by assumptions about consumers' spatial behaviour and decision making. With appropriate calibration against observed data, spatial interaction models are widely used as a predictive tool to forecast and predict consumer flows and store revenue. They are thus a valuable tool to investigate the impact of supply side interventions (such as new store development) on consumer flows, store performance (such as revenue and market share) and competitor performance. Section 2.4.1 begins with a very brief overview of the development of theory surrounding spatial interaction and subsequent development of SIM for application in retail location planning.

2.4.1 Theory of spatial interaction

A full or comprehensive review of the development of spatial interaction as a tool for location-based decision making is well beyond the scope of this thesis. Such a review has been comprehensively covered elsewhere. For example, the excellent overview by Roy and Thill (2004) charts the development of spatial interaction models in regional science, drawing examples from retail location planning, whilst Batty (2007) gives a succinct overview of the development of SIM in Geography. Birkin and Clarke (1991) also give an accessible overview of SIM for retail applications, whilst Birkin *et al.* (2010a; 2010b) review the application of SIM in applied contexts.

SIM has developed from interdisciplinary links between geography and other sciences during an era when geography was largely viewed as a quantitative spatial science. Fotheringham (2013) asserts that the SIM has gone on to become one of geography's most successful applications outside academia, with wide-ranging commercial applications, including those within location-based modelling. The earliest applied spatial interaction models were derived from Newtonian analogies and referred to as 'gravity models', with three main components: supply, demand and spatial interaction (the latter representing flows). In a generic form, a basic SIM could be written:

$$T_{ij} = k \, O_i \, D_j \, f(C_{ij}) \qquad\qquad (2.1)$$

Where: T_{ij} represents the interaction/flows between origin i and destination j

k represents a constant of proportionality

O_i is the 'mass term' associated with origin zone i, representing the flows leaving origin zone i

D_j is the 'mass term' associated with destination j and represents flows arriving at destination j

f is a function of the distance term (C_{ij}) and decreases as C_{ij} increases. It is used to control the importance of distance, a tool for model calibration.

C_{ij} represents the 'cost' of travel from origin i to destination j

[Source: Adapted from Wilson (1971)]

As such, interaction (T_{ij}) is proportional to:

the flows leaving all origin zones $\quad O_i = \sum_j T_{ij}$ and; $\quad$ (2.2)

the flows arriving at all destinations $\quad D_j = \sum_i T_{ij}$ $\quad\quad$ (2.3)

Early retail applications, developed from these Newtonian analogies, include Reilly's (1929) 'law of retail gravitation', applying the gravity concept to trade area analysis and the modelling of consumer flows to competing retail 'centres' (cities). His approach estimated the probability of a consumer shopping in a particular 'centre' based on trade area analysis, recognising that larger centres will attract consumers from a greater distance and thus exhibit a larger trade area. Later applications, such as Huff (1963), were more behavioural in nature, considering competition and consumer choice between alternative shopping centres, determining overlapping catchment areas and reflecting the notion that consumers choose between competing centres based not only on distance, but also on factors such as size and range of products.

These Newtonian analogies had a long association with regional science and transport planning, yet a variety of users, especially transport planners, identified a number of weaknesses within the models. Senior (1979) summarises that the Newtonian approaches were wholly aggregate, based entirely on a physical law without appropriate socio-geographic justification. The gravity model was noted to have a poor forecasting capacity, with a doubling of the origin population and destination attractiveness resulting in a quadrupling of flows (rather than a doubling as expected) (Senior, 1979). The early models were also incapable of predicting interactions that were consistent with known information about the system being modelled, termed constraints. As such, the Newtonian model was modified to overcome some of these issues, via the introduction of constraints, by relating aggregate behaviour to underlying individual behaviour, and modifying the handling of 'distance'.

Hugely influential work by Alan Wilson in the late 1960s and early 1970s developed SIM within geography, replacing the Newtonian gravity analogy with models derived from the principle of entropy maximisation (developed from statistical mechanics). Longley (2004)

asserts that it is around this time that models, as simplifications of reality, became commonly accepted within human geography, based on mathematical and statistical relationships between attributes at a range of spatial scales. This approach generated internally consistent models via the introduction of constraints and balancing factors, which overcame some of the criticisms surrounding the models aggregate nature and poor forecasting capacity. Entropy maximisation seeks to replicate known macro-level constraints (such as total expenditure available within origin demand zones), by producing expenditure flows (from demand zones to stores) that are consistent with these constraints whilst being as unbiased as possible about the unknown micro-level (individual) flows, thus maximising the range of possible flows and consumer choice (Roy and Thill, 2004; Senior, 1979; Wilson, 1971; Wilson, 2010).

Wilson (1971) coined the term 'family of spatial interaction models' based on the application of these constraints within entropy maximising models. He proposed a family of four models;

    a) Where neither O_i or D_j are known, the model takes an unconstrained form;

    b) Where O_i is known, the model takes a production-constrained form;

    c) Where D_j is known, the model takes an attraction-constrained form, and

    d) Where both O_i and D_j are known, the model takes a doubly-constrained form.

Wilson (1971) asserts that where O_i or D_j are unknown, they can be replaced with an attractiveness term, which is used to determine the unknown flows. In retail applications, origin zone totals (representing available expenditure) are known and as such, retail models commonly take the form of a production-constrained model, such that trip ends (and thus store revenue) can be calculated. The mass term (D_j) in retail applications is commonly replaced by a representation of store attractiveness, traditionally store floorspace. In this context, expenditure flows leaving any origin zone (i) are constrained such that they represent the total expenditure or demand available in that zone, whilst the expenditure flows arriving at any retail destination (j) are unconstrained and related to relative store attractiveness and accessibility. The remainder of this discussion considers the production-constrained SIM, which Wilson (1971) notes is particularly important for its role as a location model, and the typical notation employed for retail modelling will be adopted.

2.4.2 The classic production-constrained entropy model for retail applications

The classic production-constrained entropy maximising SIM for retail applications typically takes the form:

$$S_{ij} = A_i O_i W_j \, exp^{-\beta C_{ij}} \qquad (2.4)$$

Where: S_{ij} represents the expenditure flow between demand zone i and store j

A_i is a balancing factor which takes account of competition and ensures that all demand is allocated to stores within the region. It is calculated as:

$$A_i = \frac{1}{\sum_j W_j \, exp^{-\beta C_{ij}}} \hspace{2cm} (2.5)$$

O_i represents the demand or expenditure available in residential zone i

W_j accounts for the attractiveness of store j, and is commonly represented by the store floorspace.

$exp^{-\beta C_{ij}}$ is the distance deterrence term, incorporating $-\beta$, the distance decay parameter, C_{ij}, the distance between zone i and store j and an additional constraint related to the 'cost' of distance via the exponential function.

(Source: Adapted from Birkin and Clarke, 1991; Birkin *et al.*, 2002; Wilson, 1971; Wilson, 2010)

A basic version of the production-constrained entropy maximising model, as applied to the retail sector, assumes that the demand available (O_i) within any given small area (i) is shared by competing retailers (j) in a geographically proximate area based on their accessibility and relative 'attractiveness' (W_j). In a retail context, demand is commonly represented by available consumer expenditure, calculated with reference to zonal populations and their purchasing power, derived from demographic, geodemographic or socio-economic data. Demand is usually organised around households, based on the premise that spending power is linked to neighbourhood based attributes (Birkin *et al.*, 2010a). The demand side is considered in more detail in section 2.5, and within Chapter 5.

On the supply side, it is commonly assumed that factors such as overall floorspace drive store attractiveness, with larger stores being more appealing to consumers, generally offering greater choice or value. In reality other site specific factors, including co-location alongside other stores or facilities (e.g. see Fotheringham (1983)) or within an established centre (e.g. see Birkin and Foulger (1992)), may make a smaller store relatively more attractive than its size alone would suggest. Consequently, a scorecard approach is sometimes used, relating a series of features which may include store size, layout, parking, opening hours and store frontage, combined and weighted to provide a single measure of store attractiveness (Birkin *et al.*, 2010b).

Additionally, and as outlined fully in Chapter 6, retail brand is often an important driver of consumer behaviour, with different consumers exhibiting brand preferences based on perceptions of store quality, service and price. For example, consumers tend to perceive that Sainsbury's brand has a more upmarket position than Tesco, ASDA and Morrisons, with Clarke *et al.* (2012) noting that consumers from more affluent areas were considerably less satisfied if they had a Tesco nearby, rather than a Sainsbury's. As a consequence, evidence suggests that consumers who shop at Sainsbury's exhibit a tendency to have travelled past an

alternative store closer to their home in order to shop at a Sainsbury's (Mintel, 2012). As explained in Chapter 6, models are often disaggregated on both the demand and supply side to account for this form of brand preference among consumers, and Birkin *et al.* (2010a) note that this is an important practical consideration when building models in an applied context.

Inherent in the design of the model is the concept that expenditure flows are driven by store attractiveness and constrained by distance, representing a trade-off between the constraint of distance and the attraction of larger stores, which may not be geographically proximate (Fotheringham and O'Kelly, 1989). Store accessibility is usually an inverse function of the relative 'cost' in terms of distance or travel time (C_{ij}), calibrated using a distance decay parameter (β). For retail applications, an exponential function is often applied and is considered to be most appropriate for analysing short distance interactions (giving less weight to longer distance interactions), such as those in an urban area. (Birkin et al., 2002; Birkin et al., 2010a; Fotheringham and O'Kelly, 1989; Wilson, 1971; Wilson, 2010).

β reflects the relative importance of distance and influences how responsive changes in interaction (consumer flows) are to changes in spatial separation (Senior, 1979). It thus reflects the willingness or ability of consumers to travel to stores, recognising that consumers' propensity to travel to the store of choice may be restricted by availability or cost of transport, for example. Again, and as explored fully in Chapter 6, these models are often disaggregated by consumer type, to account for the propensity of certain consumer groups to travel further to shop at the store of choice.

To be used in a predictive capacity, such as for store-level revenue estimation, these models require calibration. Calibration involves the application of model parameters, such that the best fit between the model predictions and the observed flows or store revenue can be obtained. Calibration makes use of actual customer data such as that collected through loyalty cards, so that consumers' trip-making behaviours can be replicated, often achieved using indicators such as consumers' average trip distance, and assessed by testing for goodness-of-fit using a range of statistics, as explored fully in Chapter 6.

Based on their 2010 survey of location planning departments, Reynolds and Wood (2010a) suggest that around two thirds of retail location planning teams (across all sectors) make use of SIM for location planning. Survey respondents identified that such models had become a flexible and increasingly accurate tool for revenue estimation, adding complexity and sophistication to location analysis (when compared to analogue approaches), accounting for expenditure flows over space that result from consumers decision making processes. Birkin *et al.* (2010a) assert that one reason why these models may have become so popular in an industry context is because the clear return on investment achieved through using these models can be quantified in terms of the accuracy of predictions relative to alternative/existing methods. Birkin *et al.* (2010b) cite one example, based on a major DIY retailer in the UK, whereby an investment in spatial modelling reduced the margin of error in

their new store revenue forecasts from 30% to 10%, giving the company confidence to invest in 25 new stores over a 5 year period, generating profits of around £40m. This example clearly demonstrates that investment in this form of modelling can be used to consistently achieve robust predictions of store revenue at the pre-investment stage, allowing investment decisions to be made with confidence.

Having briefly reviewed the characteristics of these models in an applied context, attention now turns to the application of SIM within retailers such as Sainsbury's, identifying the role of this form of modelling in generating revenue predictions and some of the limitations inherent in the model, particularly identifying the demand-side weakness to be addressed in this thesis. More theoretical aspects of the production-constrained entropy maximising model as applied to grocery store location planning are also considered in Chapter 6, where a SIM is built from scratch for applied use for retail store location planning in Cornwall (Chapter 7) and subsequently Kent (Chapter 8).

2.4.3 Sainsbury's spatial interaction model

In Sainsbury's context, their SIM, termed 'Grocery Store Potential Model' is used for store revenue forecasting. The model has been developed in house, and whilst access to the model (or detail of the specific parameters used) has not been made available (for confidentiality reasons), Wright (2011) explains that the model incorporates estimations of overall household level consumer demand. Available consumer expenditure is derived using counts of residential households and associated estimates of their expenditure, based on geodemographic indicators and surveyed food spend (explored further in Chapter 5). On the supply side, their model is based on knowledge of their own and competitor estates, with store attractiveness driven by store size. They also consider relative store attractiveness in terms of how well the Sainsbury's brand fits the demographic and socio-economic characteristics of a given store catchment area (Wright, 2011), recognising that the Sainsbury's brand is often relatively more attractive to affluent consumer groups.

According to their post-investment review (after proposed stores proceeded to construction), Sainsbury's model has been found to estimate store revenue to within 10% of observed values, around 70% of the time (Wright, 2011). This performance is below the requirement imposed by the Sainsbury's board which stipulates that all forecasts should be within 5% of the store's subsequent observed trading patterns (Wright 2011). Based on their industry experience from Sainsbury's and Tesco, Wood and Tasker (2008) suggest that a 10% variation in sales forecast for a medium-sized store could influence how much a retailer is willing to bid for an individual site by up to £5m. Accurate revenue predictions are therefore essential.

Since the 'Grocery Store Potential Model' is not currently able to predict store revenue to an acceptable level of accuracy, it is used only as the first stage of revenue estimation and potential site screening by the Sainsbury's team. The revenue estimates generated by the

model are used as a guide to likely trading potential, but require considerable adjustment by analysts, utilising a site visit and comparison with a number of analogue stores to fully assess the trading potential of a site (Feltham and Davis, 2010; Wright, 2011). Drawing on experience across the industry, (Harries (2010); Reynolds and Wood (2010b); Reynolds and Wood (2010a); and Wood and Tasker (2008)) identify that this is common practice, with the site visit, analogue approaches and analyst skill remaining important 'tools' within store location planning and revenue estimation.

Wright (2008) notes that the site visit is used to identify factors which are difficult to incorporate within the model such as pitch quality, access and visibility or proximity to other complementary or competing stores. On the basis of these site visits, suitable analogue stores can be identified, allowing the impact of these factors to be inferred and incorporated within the model. Yet, even after accounting for these factors, post-investment review of modelled and observed trading performance identified that the 'Grocery Store Potential Model' still exhibited a tendency to under-predict store revenue in certain areas, limiting the strategic and operational decisions that can be based on these sales forecasts. This is particularly true in areas with a high proportion of non-residential demand, including workplace populations, students and tourists. As such, additional adjustments to the model forecasts are often applied by analysts to account for demand-side weaknesses in the modelling.

This section has demonstrated that SIM has become an important tool for store revenue estimation within the grocery sector. Site location research is recognised as an important strategic and operational function, yet inherent demand side weaknesses in the handling of non-residential demand have been identified, as explored in section 2.5.

2.5   Demand-side weakness in handling visitor demand in store-location planning

Drawing on industry evidence, Section 2.4 highlighted that the spatial modelling and revenue forecasting tools employed by retailers such as Sainsbury's may exhibit an inherent demand side weakness in their handling of non-residential demand. Birkin *et al.* (2010a) suggest that many retailers struggle to account for non-residential demand in their location-based modelling. For example, in some of their early retail modelling work with the UK high street retailer WHSmith, they note that their attempts to predict store revenue for stores in tourist centres such as York (a historic urban area) and Newquay (a popular coastal resort, see Chapter 4) were hampered by the tourist populations present in these store catchment areas. They noted in particular that their model exhibited pronounced seasonal variations in terms of its performance, with the influx of tourists or students driving additional demand uplift at certain times of the year.

As noted in section 2.4.3, the Sainsbury's Location Planning team report similar seasonal variations in the performance of their 'Grocery Store Potential Model', with the degree of

over or under estimation of store revenue fluctuating at different times of the year. In particular they note that stores located in coastal tourist resorts in areas such as Devon and Cornwall (South West England), parts of the south coast (including Kent, Hampshire and Dorset) and stores in close proximity to national parks, such as the Peak District, exhibit a pronounced seasonal trade pattern (Feltham and Davis, 2010). Given the nature of these areas as important tourist destinations (see Chapters 3 and 4), they believe that this uplift is attributable to tourists. Some stores in these areas were found to exhibit a highly seasonal sales pattern (as explored fully in Chapter 4), with sales uplift thought to be driven by a seasonal influx of visitors during the peak tourist season, boosting local demand in a way that the SIM could not handle. The 'Grocery Store Potential Model' is based on demand side estimates of residential demand. Non-residential demand driven by tourism is not incorporated. It is the inherent weakness in handling this form of demand within the store revenue estimation process that forms the basis of the work reported in this thesis.

Section 2.5.1 identifies the nature of tourist demand and its impacts at a store-level. Tourism itself is introduced fully in Chapter 3, whilst store-level impacts are considered further, with reference to empirical data from Sainsbury's, in Chapter 4.

2.5.1 Tourism as a driver of store-level grocery demand

Reference to the established literature identifies that supermarkets and other grocery stores can form an important part of service provision in tourist resorts. This is particularly true where self-catering accommodation provision is dominant (Dudding and Ryan, 2000; Timothy, 2005) since, by-definition, these visitors have a tendency to purchase food and drink for consumption within their accommodation. Common sources of food for visitors include restaurants, pubs and cafes, although the range of food and drink sources used by tourists is often more complex. Dudding and Ryan (2000, p302) state that "not all such eating out occurs in restaurants normally associated with tourist developments .... tourists may use fish and chip shops, pubs, Chinese take-aways and similar low-cost sources of food, including fast food outlets". They go on to note that "in many holiday locations, during the summer season tourists will complement revenue derived from residents for a range of retailers such as supermarkets, chemists, newsagents, pubs and cafes" (Dudding and Ryan, 2000, p302). Recent visitor surveys and research (explored fully in Chapters 3 and 5) identify that visitors generate considerable expenditure within their destination on food and drink purchased from grocery stores (BH&HPA, 2012; CCC, 2007; Holidaylettings.co.uk, 2008; Mottiar, 2006; Quinn, 2010).

There has been surprisingly little academic focus on visitor expenditure within grocery stores, yet these stores are relied upon by visitors and often experience considerable seasonal sales fluctuations driven by visitor demand (illustrated in Chapter 4). There is very little evidence that retailers have begun to address long-term, store-wide seasonal demand uplift as experienced around stores in tourist resorts, even though concerns about the operational

impact have been noted. Drawing on examples from Cornwall, a popular destination in the UK for highly seasonal domestic tourism (which is the basis for the analysis and modelling carried out in Chapters 4 – 7 and is introduced fully in Chapter 4), the store manager at a Tesco store in the town of St Austell outlines operational concerns in her store. She claims "We are quite a unique store in that we are very seasonal, with holiday makers in the summer visiting the Eden Project [a major nearby attraction] and other facilities and we have a major role in making sure that they stay and shop in the area. However, due to constraints over shelf space we are not able to stock high volumes of seasonal stock" (DPPLLP, 2009, p26). The store manager highlights her belief that the store plays an important role in retaining expenditure associated with tourists visiting local attractions and outlines the difficulties that the store faces in meeting some of the existing demand.

A store nearby in Wadebridge "provides a key facility for shoppers within the catchment and a number of shoppers (resident and tourists) from beyond the catchment" (API, 2010, p2). A planning application for an extension at this store outlines that the store and car park are extremely congested during the summer months, and that the store fails to keep up with demand, struggling operationally to restock shelves and manage queues, ultimately resulting in a poor customer experience (API, 2010). At another store in the popular resort of Padstow, Tesco has taken temporary steps to address operational issues driven by seasonal demand inflow. The company has located a temporary 'seasonal/summer store' in a 500 Sq Ft marquee in the store car park during the summer months (Maguire, 2010). This highlights that the store struggles to meet the needs of customers during the summer and needs additional floorspace to stock seasonal items and ease congestion in-store. This store is considered further during the supply side modelling carried out in Chapter 7.

These examples highlight that the focus among retailers seeking to address seasonal demand uplift, driven by tourism, has been on managing operational impacts such as stock replenishment during these periods. However, the impact of this form of demand on overall store revenue, and the inability of retailers to accurately estimate store revenue in tourist areas highlights that seasonal demand uplift driven by tourism is not solely an operational issue. The difficulties in accurately predicting this form of demand uplift (which may be sustained across the whole summer tourist season) is likely to impact upon strategic decision making, including overall network planning and the evaluation of individual store development opportunities. Section 2.5.2 outlines some of the crude approaches that have been used to account for this form of demand uplift in location-based modelling.

2.5.2 Incorporating visitor demand in store revenue estimation

Aside from analogues with existing stores, the literature reveals very few established methods for estimating visitor demand for use in grocery store location planning. Limited evidence (obtained through store planning applications) suggests that a common approach involves the simple up-scaling of modelled revenue estimates (based on residential demand)

in an attempt to account for tourist expenditure. As noted further in Chapter 4, a predetermined uplift factor is often used, with recent store development proposals (in tourist resorts within Cornwall), employing tourist demand uplift factors of between 15% and 30% (API, 2010; API, 2011; API, 2012). For one such proposal (for a store extension in the town of Wadebridge, Cornwall), a detailed and robust assessment of the potential revenue available from local residents was undertaken, and at the final stage of revenue estimation, a 30% demand uplift was added to the revenue predictions in an attempt to account for visitor spending.

As illustrated fully in Chapters 4 and 5, this approach is crude and could be misleading as it assumes that the spatial distribution of visitor demand is closely related to the spatial characteristics of residential demand. No attempt to determine the spatial or seasonal characteristics of visitor expenditure is involved, and the upscale factors simply represent a judgement based on analyst observations of the potential catchment, and knowledge from analogue stores. Visitor accommodation, a key driver of visitor grocery expenditure, tends to exhibit a high degree of spatial clustering (see Chapter 5). Simply up-scaling (at an aggregate level) to account for visitor demand lacks insight into the local spatial and temporal pattern of visitor demand and does not represent a robust methodology for incorporating seasonal visitor expenditure uplift within store revenue estimation.

Limited evidence from industry contacts and from an anonymous referee[2] suggests that, in some cases, location planners have experimented with attempts to incorporate some visitor-driven expenditure within the spatial modelling process itself. For example, some location planners may identify key accommodation sites (such as large holiday parks) within proposed store catchment areas and manually input additional demand associated with these sites within their demand side inputs to the SIM. Whilst this allows location planners to take account of the spatial distribution of key visitor accommodation sites, difficulties in identifying expenditure rates or accounting for seasonal variations in visitor numbers using these sites may currently limit the insight gained from this approach. Nonetheless, this suggests that retailers are actively seeking to improve the forecasting capacity of their models.

Wood and Reynolds (2011) note that many retail location planning teams are under-resourced, and so the capacity to develop these techniques is likely to be limited. This section has outlined that visitor demand is an important driver of store-level revenue in tourist resorts, yet this form of demand is not currently handled effectively within the spatial modelling tools used by retailers for site evaluation, setting the context for this study, summarised in section 2.6.

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[2] In response to a paper based on this work and submitted to the International Review of Retail, Distribution and Consumer Research.

2.6 Conclusions

This chapter demonstrates that continual growth and intense competition for market share within this sector (section 2.2) has encouraged grocery retailers to invest heavily in location planning (section 2.3), which benefits from sophisticated spatial modelling to forecast store revenue, taking account of the characteristics of consumer demand and retail supply (Section 2.4). Whilst retailers such as Sainsbury's have a well-developed suite of spatial modelling tools and consumer data available, they note that their SIM cannot account for the full range of store and catchment specific factors that influence consumer demand and store revenue. In particular, an inherent weakness in the demand side handling of highly seasonal visitor demand has been noted, with clear implications for store revenue estimation. Tasker and Wood (2008) identify that retailers are increasingly willing to invest capital in order to improve the capacity to accurately forecast revenue for new store investment, thus reducing the level of risk involved in that investment. This thesis represents one such 'investment' on the part of Sainsbury's.

This thesis seeks to embed seasonal demand uplift (attributable to visitors) within the demand-side expenditure estimation used as input to SIM. As such, and as outlined fully in Chapter 1, this thesis seeks to develop a series of seasonal demand layers and an associated SIM that can be used by retailers such as Sainsbury's to generate store revenue predictions, accounting fully for the impact of spatial differences in the number of visitors and their associated grocery expenditure at different times of year. Chapter 3 seeks to provide further context, introducing the tourist sector and considers the role of visitor demand in driving store-level revenue fluctuations in the grocery sector, noting the seasonal and spatial variations inherent in visitor expenditure and identifying the difficulties in obtaining small-area indicators of seasonal visitor-induced demand.

Chapter 3: Tourism as a driver of local seasonal and spatial variations in grocery demand

3.1 Introduction

In a 2010 review by audit company Deloitte, the tourism sector contributed £115bn to UK GDP, supported over 2.6 million jobs, and represented the fastest growing economic sector (Deloitte, 2010). High profile events such as the Olympic and Paralympic games have continued to boost inbound tourism (overseas visitors), though much of the growth in this sector is driven by domestic tourism, particularly as households forgo overseas holidays on financial grounds and instead enjoy their main holiday within the UK (which has become termed the 'staycation') (VisitBritain, 2010). Unlike international tourism (which is concentrated on key destinations such as London), domestic tourism is driving demand for breaks in coastal and countryside areas, with coastal resorts enjoying much of this growth in visitor numbers (DCMS, 2007). Chapter 2 noted that grocery stores make up an important part of service provision within tourist resorts. Additional seasonal demand uplift, driven by tourists, may generate seasonal revenue fluctuations at grocery stores in these resorts. The handling of this form of demand within location-based modelling represents a current weakness which this thesis seeks to address.

As explored fully in this chapter, visitor expenditure plays an important role in local economies. However, the contribution of spending on groceries is often underestimated or overlooked when considering the local economic impact of tourism. It is also poorly handled when making location-based decisions about service provision and retail store location in tourist resorts. This chapter situates the thesis within a broader understanding of the tourist sector and the discussion that follows seeks to define and contextualise tourism in the UK, considering both the demand and supply side. Section 3.2 introduces a broad categorisation of visitors by origin and trip purpose, identifying their importance to UK tourism and their key seasonal and spatial patterns. The discussion briefly considers the development of (coastal) tourist resorts. These represent highly seasonal spatial clusters of visitor demand and form an important part of the modelling addressed within this thesis.

Section 3.3 focusses on collecting data on visitor demand, and outlines the key national sample surveys that provide headline figures on visitor numbers and their associated characteristics at a national or regional level. Section 3.3 notes, however, that very little is known about visitor numbers, their expenditure or economic impact at the local level. Local insight is often reliant on costly and unreliable or outdated survey data. Section 3.4 presents a series of economic impact models that are commonly employed to disaggregate national survey data to the local level, identifying the impact of tourism on local economies. These models recognise the importance of accommodation stock in determining seasonal and

spatial patterns of visitor expenditure. Section 3.5 considers the role of accommodation further, outlining the impact of accommodation type on seasonal and spatial patterns of visitor demand, drawing on data from key national surveys, academic literature and ad-hoc industry research. Visitor expenditure on groceries is also introduced in section 3.5, building upon the discussion in Chapter 2, noting that very few studies have considered the grocery expenditure associated with different types of visitor. Nevertheless, the impact of trip purpose and accommodation on grocery spend is outlined as a basis for the analysis of visitor spend in grocery stores (presented in Chapter 4).

3.2   Defining and contextualising tourism in the UK

Tourism is considered to be a demand side concept. The sector is "defined by the activities of tourists and what they spend their money on" (Buccellato *et al.*, 2010b). Tourists are, however, difficult to define. An agreed definition by the United Nations World Tourism Organisation (UTWTO), the Organisation for Economic Co-operation and Development (OECD) and the Statistical Office of the European Communities, suggests that tourists can be thought of as agents in an interaction process linking origin and destination[3]. The current definition (UNWTO, 2008, p10) (which itself replaces an earlier definition (UNWTO, 1994) which was commonly accepted within the literature and adopted by the UK Government (DCLG, 2006)) identifies that "A visitor is a traveller taking a trip to a main destination outside his/her usual environment, for less than a year, for any main purpose". Further clarity is provided, stating that "A visitor (domestic, inbound or outbound) is classified as a tourist (or overnight visitor) if his/her trip includes an overnight stay, or as a same-day visitor". Within this definition, traditional conceptions of visitors being holiday-makers can be considered alongside other diverse activities that visitors undertake (for example shopping, attending sports events, visiting friends and relatives or attending conferences), so long as these activities take place outside an individual's 'usual environment'. The terms 'staying' and 'usual environment' are interpreted fairly liberally within the literature such that a broad range of activities and types of visit, including day visits (without an overnight stay) to destinations and attractions close to home, represent a form of tourism (Bryan *et al.*, 2006; EUROSTAT *et al.*, 2001).

On the supply side, the tourism sector represents all the businesses and organisations that supply goods and services which meet visitor demand. Drawing inferences about tourism from the supply side is, however, complex. Tourism is not easily identifiable via specific

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[3] Other forms of spatial interaction between an origin and destination, such as daily commuting, long-term migration, or other forms of travel (such as through the armed forces) do not count as visitors in studies of tourism and are not considered further within this thesis.

supply side industries. Visitors spend money in a range of businesses, supporting industries traditionally thought of as part of the tourist sector, such as accommodation, tour operators and some transport services. Visitors also make up a proportion of demand in other businesses and services which are not commonly associated with tourism, such as grocery stores (which are primarily considered to be meeting residential demand). As such, visitors account for only a proportion of the total demand in any tourism-related industry or service, with the remainder being attributable to residents (Beatty *et al.*, 2010; Buccellato *et al.*, 2010b). The tourism 'product' is not distinct (on the supply side), and identifying the impact of visitor expenditure on local economies and specific industries can consequently be problematic.

Little is therefore known about how much value is generated by tourism at the local level or within specific sectors such as the grocery market. This chapter attempts to unpick some of the seasonal and spatial driving factors behind this form of visitor spend at the local level. The following sections briefly explore further the understanding of tourism in the UK as a demand side concept, considering the different types of visit that constitute tourism, identifying some of the seasonal and spatial patterns inherent in visitor demand (section 3.2.1) and outlining the growth of tourist resorts (where supply and demand interact) (section 3.2.2).

3.2.1   A demand side understanding of tourism

Taking the demand side definition introduced above, tourism can be seen to encompass a range of activities and trip purposes, attracting a broad range of visitors, each of which are likely to generate very different spatial and temporal characteristics and associated consumption. In order to identify the economic impacts of tourism, visitors are commonly segmented into a number of clearly identifiable groups, based either on their own characteristics, or characteristics of their visit. Within the literature, industry insights and destination-level surveys of visitors, visitors are commonly segmented based on their demographic or socio-economic characteristics, nationality or spatial origin. Often the National Readership Survey (NRS) social grade classification is used (Williams, 2008), as applied and explored further in Chapter 4. This type of segmentation has largely developed as a tool to assist tourist organisations to market destinations (which could be a nation, region, individual resort or attraction), focussing resources on the profile of visitors that a destination attracts (Svensson *et al.*, 2010; Thornton *et al.*, 1997; WTO and ETC, 2007). Thus, segmentation is used as a tool to target visitors that have a higher overall expenditure, such that the overall capacity within a destination or attraction is used to maximum benefit (Svensson *et al.*, 2010).

In collecting data on visitors and their associated expenditure, a clear distinction is made between inbound (international) visitors, domestic overnight visitors and day visitors (Figure 3.1). Visitors are also commonly segmented by the purpose of their trip. This is

recognised to have a clear impact on seasonal and spatial patterns of visitor expenditure (Charles-Edwards, 2011).
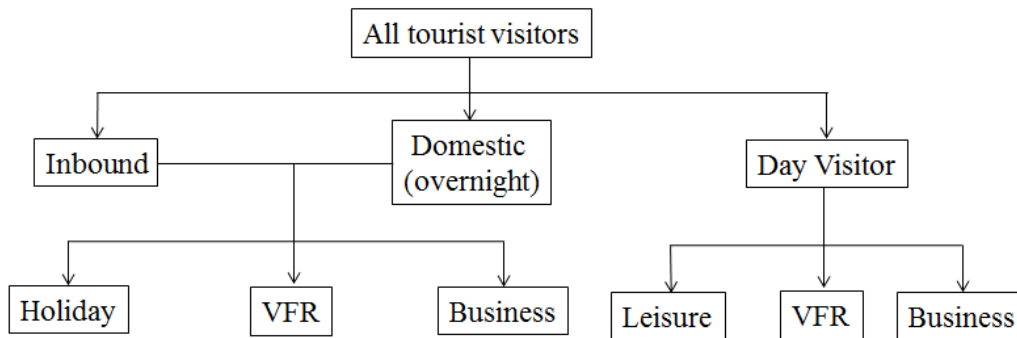
Figure 3.1 - Segmentation of visitors by origin and trip purpose

Inbound tourism (representing foreign nationals visiting the UK) is an area where the UK has traditionally been strong, driven in part by the large number of ex-pats returning to visit friends and relatives (WTO and ETC, 2007). Active marketing by national and regional tourist organisations (particularly during the 2012 Olympic Games), and the relatively weak value of Sterling (which boosts inbound tourism) have driven growth in this sector. However, UK Government Tourism Policy (DCMS, 2011) clearly identifies that domestic tourism is "far larger and more important to the [tourism sector] overall", particularly since domestic tourists exhibit a far greater propensity to contribute to demand across the UK's regions. Domestic visitors generate expenditure in coastal and countryside areas alongside major cities and attractions, which are a key focus for international visitors (DCMS, 2011). The domestic tourism market is important not only for its overall contribution to tourist spend in the UK (with Mintel (2011a) analysis forecasting a 5.7% increase in spend on domestic trips up to 2016), but also as a driver of grocery spend by tourists (most notably for self-catered trips (Timothy, 2005)).

Figure 3.2 illustrates the spatial distribution of domestic (overnight) trips in England at the regional level. Data has been drawn from the UKTS (see section 3.3.1.2) and is broken down by trip purpose, based on the headline categories of Holiday, VFR and Business tourism. Over 25% of both holiday and VFR trips by UK residents are to the South West region, which incorporates popular coastal destinations within the counties of Cornwall, Devon, Dorset and Somerset. The South East also attracts over 15% of domestic holiday visits and around a quarter of business trips. Other regions generally attract between 5% and 15% of the total domestic tourism market (by number of trips) highlighting the importance of domestic tourism in supporting regional economies in the UK.

Domestic visits, especially those that represent holidays, tend to exhibit a pronounced seasonal distribution, peaking during the school summer holiday period (August) (Figure 3.3). Based on data relating to 2010, Figure 3.3 disaggregates holiday trips into those of three nights or less (short breaks) and those of over 4 nights. Holidays over 4 nights

demonstrate a very clear seasonal distribution, with over 60% of these trips starting between July and September. By contrast, business tourism tends to peak in the low season (e.g. February), whilst VFR experiences considerable uplift at Christmas. These seasonal variations are driven by interrelated demand and supply side factors. These include the weather, the institutional calendar (timing of national holidays, major religious festivals and school or university term dates), local events and festivals and the seasonal availability of key visitor facilities and services, such as accommodation. It is these seasonal variations that impact upon the trading performance of stores in major resorts.
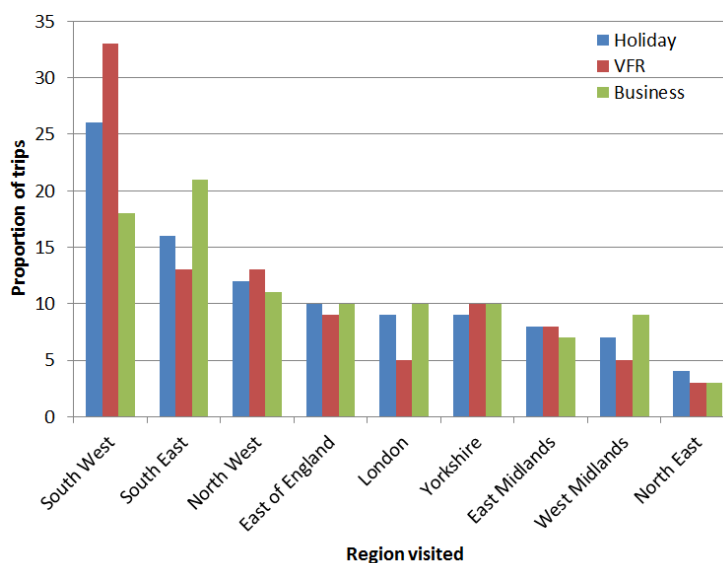
Figure 3.2 - Spatial pattern of domestic tourism (England) by number of trips

Source: UKTS (2010) extracted via online data browser: http://dservuk.tns-global.com
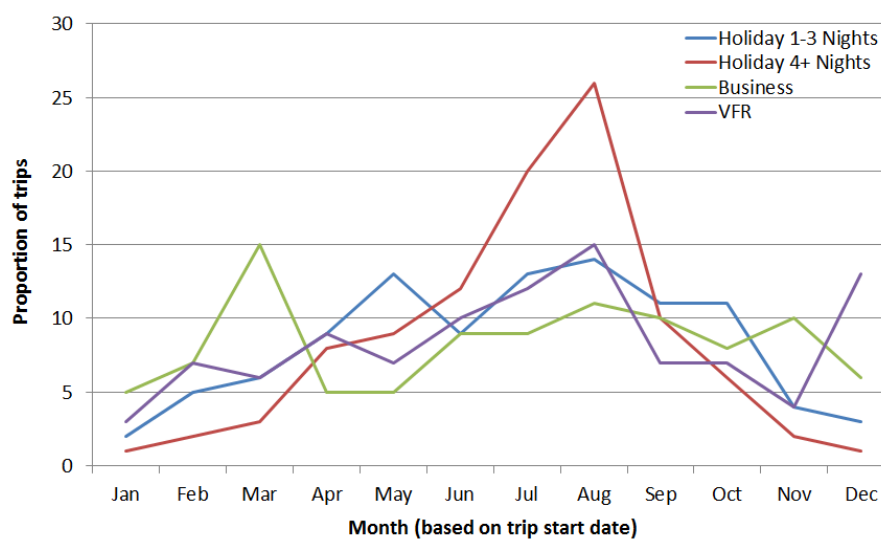
Figure 3.3 - Seasonal pattern of domestic tourism (England) – visits to the South West region by trip purpose (2010)

Source: UKTS (2010) extracted via online data browser: http://dservuk.tns-global.com/

Domestic visitors also make use of a broad range of accommodation which, in turn, gives rise to a complex range of seasonal and spatial patterns in visitor expenditure at the local level. Considering just the South West region, the accommodation used (by trip purpose) is outlined in Table 3.1. Within the South West, it is clear that self-catering accommodation (especially camping and caravanning) are important, together accounting for almost 60% of holiday trips. It was noted in Chapter 2 that visitors using these forms of accommodation are most likely to generate expenditure within grocery stores. By contrast, business travellers show a tendency to favour serviced accommodation. Each form of accommodation exhibits its own spatial distribution and seasonal occupancy patterns within a destination, giving rise to localised seasonal and spatial patterns of visitor expenditure (as explored throughout this thesis).

Table 3.1 - Accommodation usage by trip type for domestic visitors (England) to the South West region (2010)

	% of trips by accommodation type		
Type of Accommodation	Holiday	VFR	Business
Hotels and guesthouses	24	11	50
Self-catering	26	2	3
Camping & Caravanning	32	3	13
Hostels	1	0.5	1
Own home/friends or relatives home	15	84	14
Other	1	0	19

Source: UKTS (2010) extracted via online data browser http://dservuk.tns-global.com/

Day visitors are also recognised to be an important part of UK tourist demand, contributing over £40bn annually to the economy (DCMS, 2011, p45). Day visits may be for leisure or business purposes and include visits to city centres for shopping, trips to visit friends and relatives, visits to take part in outdoor activities or for sightseeing (White, 2010b). Day visitors are particularly important during local events and festivals, where they are often found to significantly boost visitor numbers. Whilst their economic contribution is important, day visitors are difficult to identify, consumption habits are hard to ascertain and these visitors have traditionally been underrepresented in the major tourism surveys carried out in Great Britain (see section 3.3.1.3).

As well as exhibiting a clear seasonal distribution, domestic tourists (both day and overnight visitors) show a tendency to cluster around key destinations such as coastal resorts, generating local-level expenditure uplift. The growth and nature of tourism within these resorts is considered in section 3.2.2.

3.2.2 Tourist resorts – the interaction between tourism demand and supply

The discussion that follows highlights some of the key characteristics of tourism supply and demand in the UK, focussing in particular on the growth of (coastal) tourist resorts as important destinations for highly seasonal domestic tourism. Resorts represent receiving areas for large numbers of visitors and their associated expenditure. They exhibit spatial clusters of accommodation, visitor facilities and attractions (Gordon, 2000) and represent a major part of the supply side in this sector. The examples presented in subsequent Chapters (drawn primarily from Cornwall and East Kent) consider a range of coastal resorts as key tourist destinations all of which are highly seasonal in nature. In these resorts, seasonal expenditure inflow often boosts local demand, supporting employment, the development of infrastructure and the provision of local services, many of which would not be viable based solely on residential demand. This section briefly highlights the factors that gave rise to the growth of coastal resorts as highly seasonal tourist destinations, considering the nature of contemporary tourist demand in these resorts.

In the UK, mass demand for tourism developed as a product of the industrial revolution, accompanied by the introduction of an annual holiday taken by the working classes. Whole towns (or manufacturing industries) would shut down for a week in the summer whilst staff holidayed, recognised by factory owners as 'wakes weeks' (Urry, 2002). The expanding railway network facilitated movement between the industrial cities and growing coastal resorts such as Blackpool, Skegness and Margate (Beatty *et al.*, 2008; Buck *et al.*, 1989; Dines, 2009; Shaw *et al.*, 2000), where considerable spatial clusters of tourist facilities (later incorporating major holiday camps such as Butlins) developed. This period is commonly termed the 'fordist era of mass tourism' (Lew, 2001), and it is this era that has shaped the supply of tourist facilities within the UK and investment in major (coastal) resorts. This era also drove demand for domestic tourism, instilling the concept of an annual holiday which, coupled with statutory holiday entitlement for all employees, remains important in driving seasonal demand for tourism (Thornton *et al.*, 1997).

Buck *et al*. (1989) identify that a number of factors led to the decline of the traditional seaside resorts, not least major decline in the industrial cities themselves, which were the major source of tourist flows. Tour companies and cheaper air travel expanded the appeal of overseas package holidays in the 1970s, providing direct competition for UK coastal resorts. Overseas resorts offered better facilities, better weather and lower prices (Gordon and Goodall, 2000). Whilst some former major coastal resorts remain in decline (characterised by high unemployment, ageing populations and a lack of investment) (Beatty and Fothergill, 2003; Beatty *et al.*, 2008; 2010; 2011; Walton and Browne, 2010), other destinations have experienced considerable redevelopment, and many coastal resorts within the UK are still heavily specialised towards tourist provision (Gordon, 2000). Resorts such as Blackpool,

Bournemouth and Brighton, have retained much of their large hotel stock by embracing the business and conference market, whilst others, such as Newquay (Cornwall), Weymouth (Dorset), St Ives or Padstow (Cornwall) have found niche markets (e.g. surfing, sailing, art or gastronomy) (HIL, 2005).

Coastal resorts have remained incredibly important destinations for domestic tourism. Recent research (Beatty *et al.*, 2010) notes that the seaside tourist industry remains a major source of employment, with employment in this sector increasing over the past decade, with half of the growth being in South West England. Indeed, whilst there may be widespread belief that UK coastal resorts are in decline, one of the UK's fastest growing hotel chains, budget operator Travelodge, announced (in 2008) that it planned to open new hotels in over 50 coastal resorts, citing the continuing growth of domestic tourism in these resorts as the major reason (Dines, 2009).

Figure 3.4(a) shows the location of 41 'principal seaside resorts' in England and Wales; towns with a population of at least 10,000 people where seaside tourism makes up a considerable proportion of the local economy, supported by tourist infrastructure and holiday accommodation. Figure 3.4(a) suggests that these are primarily located along the South Coast. Figure 3.4(b) shows the location of 50 smaller seaside towns in England and Wales, all of which have a considerable tourist function. Figure 3.4 identifies a number of resorts in Cornwall (including Newquay, Padstow, Bude and Looe) and East Kent (Thanet, Whitstable, Herne Bay, Deal, Folkestone, Hythe and Dymchurch). In all these locations, Beatty *et al.* (2010), p5 assert that the seaside tourist industry "remains alive and well and seems to be growing". These coastal resorts form an important part of the modelling within this thesis and are introduced in subsequent Chapters.

Changes in the nature of tourism within these resorts, particularly the type of accommodation used, reflect broader changes in tourist demand in its 'post fordist' era (Lew, 2001). A number of societal changes have given rise to increasing demand for domestic tourism. These factors include: a) rising disposable incomes, in part due to the growth in dual income households; b) a continual growth in paid holiday leave and flexible working conditions, providing more opportunities for short breaks outside the peak tourist season; c) an increasing desire to escape the pressures of everyday urban living and stressful occupations; d) increased mobility, for example through increasing car ownership, and; e) the rise in wealthy elderly populations, many enjoying good health and longer life expectancies, giving rise to expanded travel opportunities in retirement (Urry, 2002; Wall and Mathieson, 2006).
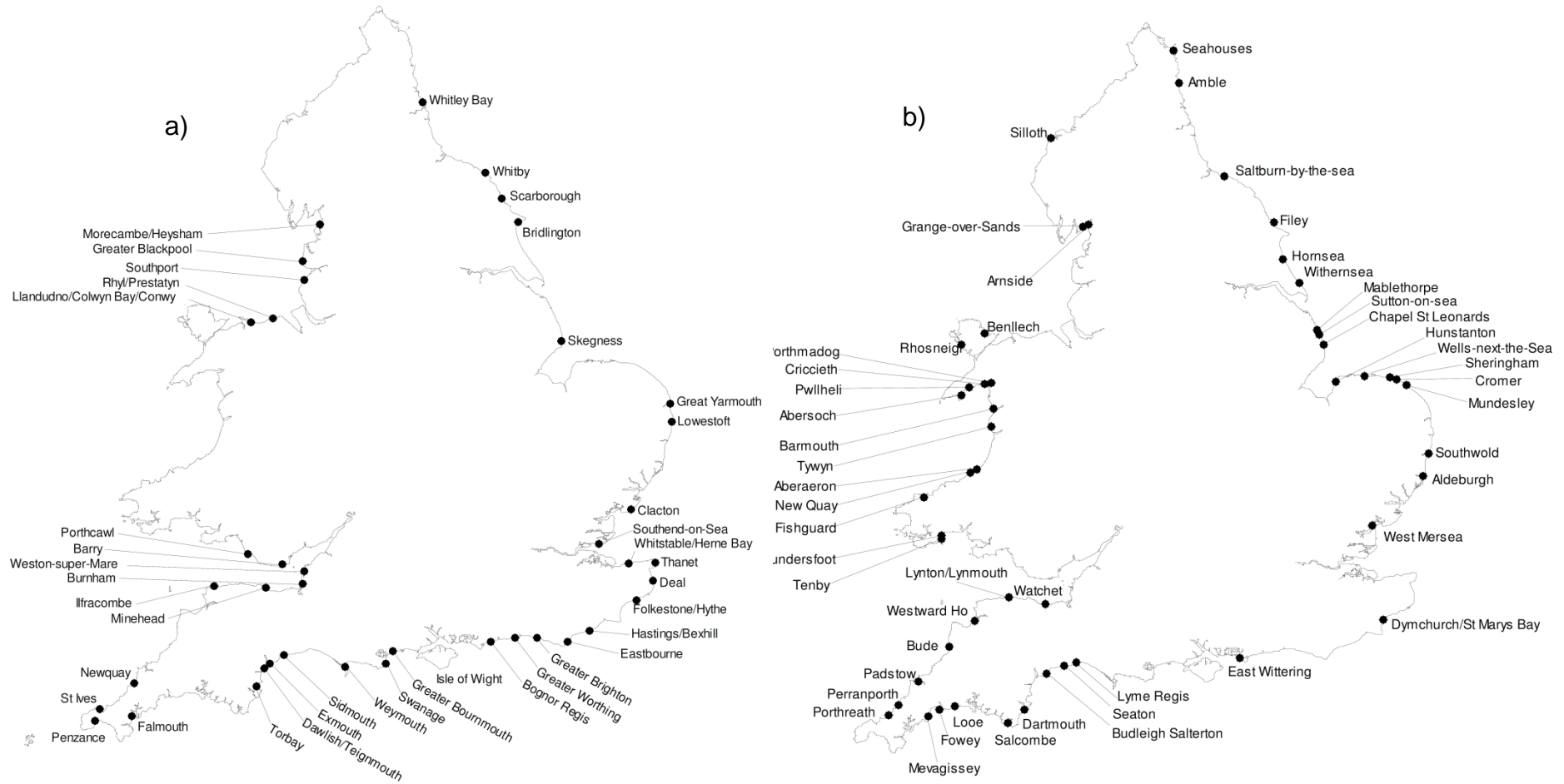
Figure 3.4 - Location of a) principal seaside resorts, and b) smaller seaside towns in England and Wales

Source: Beatty *et al.* (2010), p 16 and 19

As a result, there is an increased propensity for people to holiday out of the peak season, and for many households to enjoy a number of short breaks during the year, accompanied by a clear shift in preference away from serviced accommodation (Thornton *et al.*, 1997). Visitors exhibit a greater propensity to use self-catered, rental accommodation, typically in the form of cottages, apartments, static caravans and lodges, or caravanning and camping. Johns and Lynch (2007) demonstrate that the demand for these forms of accommodation has risen steadily since the 1970s, in part indicating a desire for greater independence among many tourists, who, by using self-catering accommodation, are "freed [from the] institutional constraints of fixed meal times" in many hotels (Thornton *et al.*, 1997, p1848). The self-catering sector, and the important role of self-catering accommodation in generating seasonal visitor grocery expenditure, is explored in section 3.5.

Having noted the importance of individual resorts as key destinations where tourist demand and supply interact, sections 3.3 and 3.4 consider some of the difficulties in obtaining reliable, timely and consistent data on the volume and value of tourism at a local level. Since this thesis aims to model small-area grocery spend associated with visitors, it is the local seasonal and spatial variations in this form of expenditure that are important. Section 3.3 identifies that a well-developed survey infrastructure exists, providing information on visitor numbers and their associated spend at a national and regional level. Whilst economic impact models are able to translate such information into local insights, section 3.4 outlines that surprisingly little is known about tourism at the sub-district level.

3.3   Obtaining data on tourist demand

Estimating visitor numbers and spending is conceptually simple, yet the actual collection of the data required to estimate and identify visitor spend, particularly at a local level, is complex (Wilton and Nickerson, 2006). Visitor expenditure is considered to be an important indicator of the economic benefits of tourism (Frechtling, 2006), and is one of the main drivers of employment in tourism (Ashworth and Johnson, 1990). As such, data on visitor expenditure is important, supporting policy makers at a national or regional level. Given that the tourist sector is difficult to identify on the supply side, much of the insight into visitor numbers (and their associated expenditure) has to be inferred from the demand side. This section first considers the range of national surveys available, allowing overall trends, visitor numbers and headline expenditure to be identified. Section 3.3.2 extends the discussion, noting that robust and timely data collection does not exist at the sub-regional level.

3.3.1   Visitor surveys in the UK

Three major national surveys provide headline figures on tourist numbers and their associated spend in the UK (international tourists) or Great Britain (domestic overnight and day visitors). In turn, these surveys feed into a series of economic impact models, used by regional and local tourist boards, counties and local authorities in order to understand the

impacts of tourism (see section 3.4). This section briefly reviews the key national surveys available in the UK or Great Britain, allowing identification of visitor numbers and expenditure associated with inbound visitors (section 3.3.1.1), domestic overnight visitors (section 3.3.1.2) and day visitors (section 3.3.1.3).

3.3.1.1 International Passenger Survey

Traditionally, organisations such as the Office for National Statistics (ONS) have placed importance on understanding expenditure associated with inbound visitors, and their impact on national or regional economies (as inbound international tourism represents a major source of income from foreign exchange) (Buccellato *et al.*, 2010b). Since 1961, the International Passenger Survey (IPS) has provided information on both inbound and outbound international tourism and is based on an interview administered questionnaire completed with a sample of around 0.2% of all travellers passing through the UK's main airports and ferry terminals (ONS, 2013). This survey provides data at a regional level relating to the number and type of inbound visitors, along with their trip characteristics and estimated expenditure, and is based on around 250,000 interviews per annum.

IPS data is not directly used in this thesis since broad trends in seasonal and spatial patterns have been derived from the UKTS/GBTS (section 3.3.1.2), as domestic visitors have a greater influence on grocery expenditure at the resort or destination level. Nonetheless, IPS data is incorporated within outputs used in Chapters 5 and 8 based on the 'Cambridge Model' (which is itself introduced in section 3.4.2.2).

3.3.1.2 United Kingdom/Great Britain Tourism Survey

The United Kingdom Tourism Survey (UKTS) provided data on domestic overnight trips undertaken by UK residents between the years 1989 and 2010. Based initially on a telephone survey, the methodology changed significantly in 2005 with the introduction of face-to-face interviews, carried out in the respondents' home (of which around 2,000 were carried out each week) (TNS, 2010a). With a sample of around 100,000 respondents per year (Visit England, 2010), participants were asked to recall specific characteristics of up to three recent domestic trips. During analysis and reporting, the data were weighted to account for the demographic, socio-economic and geographic characteristics of the population as a whole.

In 2011 the UKTS was replaced with the Great Britain Tourism Survey (GBTS) following the withdrawal of Northern Ireland from the data collection and reporting process. The survey methodology, sample size, analysis and reporting remained unchanged however, with the exception that published results no longer include Northern Ireland. Within this thesis, data from both the UKTS and GBTS are utilised in order to make inferences about the seasonal distribution of visits. Within Cornwall (Chapter 5), the year 2010 is considered and data is thus drawn from the UKTS. Within Kent (Chapter 8) the year 2011 is modelled and, as such, data is drawn from the GBTS. As the data used has been extracted from regional

tables (related to either the South West or South East region) and does not include Northern Ireland, the terms UKTS and GBTS can be used interchangeably within this thesis.

The UKTS/GBTS survey data are an immensely valuable resource to researchers and provide information on the volume and value of domestic trips. These trips are broken down by geographic hierarchy to regions and can be analysed against a broader set of variables (such as the group size, the mode of transport used or the region of origin of the respondent). Headline results are also reported on a monthly basis (based on the respondents self-reported month that a trip began). As such, seasonal distribution of trips (by month) by trip purpose, region visited or accommodation used can be identified. Unfortunately, however, and in common with most visitor survey data, the UKTS does not directly collect expenditure data on grocery spend (which is instead included alongside other forms of expenditure in the 'other shopping' category and not uniquely identifiable). Thus, whilst the UKTS/GBTS can be utilised to make inferences about trip distribution and broad expenditure associated with those visits, the level of insight provided is too broad to identify important forms of visitor consumption such as food and drink purchased from grocery stores.

3.3.1.3   England Leisure Visits/Great Britain Day Visits Survey

Day visitors are a subset of visitors that have received little attention within data collection. With the exception of a national survey carried out in 2005, little insight into these forms of visitors, or their associated seasonal or spatial characteristics, was undertaken in the 2000s. The 2005 England Leisure Visits Survey (ELVS) was led and coordinated by Natural England and carried out with the support of a number of national park authorities in England. Whilst the survey was comprehensive (for example considering both the characteristics of visitors themselves and the trips they were making), it was based on telephone interviews for only 23,500 households (Natural England, 2005). The ELVS did not form part of the national tourism data collection and was heavily focussed on particular forms of tourism (predominantly to national parks and the countryside) due to the nature of survey sponsors. It was not until 2011 that the Great Britain Day Visitor Survey (GBDVS) was launched.

The GBDVS provides the most comprehensive source of data available related to day visitors. It is based on an online survey of around 35,000 households, weighted to account for the geodemographic and socio-economic characteristics of all households and further informed by around 6,000 face-to-face household interviews (Visit England, 2013). Outputs are reported by region visited and type of activity (again by month) but, in common with the key surveys of overnight visitors, expenditure data on groceries is not explicitly collected or reported. Nonetheless, the GBTS (and in some cases the ELVS) provides useful insight into the day visitor sector and is used to inform subsequent modelling in Chapters 5 and 8.

3.3.2   Understanding tourism at the sub-regional level

Whilst comprehensive and robust, these national sample surveys offer a very limited insight into the nature of tourism at a sub-regional (county) or local authority district level, and even less so within individual resorts or destinations (Beatty *et al.*, 2010; TIU, 2011). This lack of focus on local outputs is surprising given that tourism activities have traditionally clustered around (and been dependent upon) key resorts, destinations and amenities, resulting in very localised (and often highly seasonal) economic impacts. Consequently, Bryan *et al.* (2006) note that decisions about service provision within tourist areas are often being made with very little knowledge of the extent to which visitor spending supports local economies. As such, firms and local development authorities may be making decisions about service provision with little knowledge of local visitor numbers, their seasonal distribution or the local impacts of visitor spend (see also Jones and Munday (2009)).

The lack of knowledge and insight into small-area visitor numbers is in stark contrast to the importance placed on understanding other population sub-groups. Visitors (in the form of tourists) are one component of local populations, which will also be made up of local residents alongside other visitors for work (commuters), education or other leisure and personal reasons. A robust and well-developed infrastructure exists for collecting information on small-area residential populations (via the decadal census). The census provides a snapshot of small-area populations resident in households or other similar establishments. Almost all conventional approaches to population modelling and resource allocation are based on residential locations, with sub-district population counts disseminated through a series of specially constructed hierarchical zones, the smallest representing an Output Area (OA) containing an average of 124 households (Vickers and Rees, 2006). OAs are built around residential addresses and are an important spatial scale for local-level analysis and decision making, yet very limited data relating to tourism is collected at this level. Census-derived local population estimates (and decisions about service provision that are based on them) fail to account for short-term population fluctuations driven by an influx of workers, students or visitors to particular areas at certain times of the day or at specific times of the year.

Smith and Fairburn (2008) attempted to produce a National Population Database (NPD) for use by the UK Health and Safety Executive (HSE). They attempted to incorporate populations not enumerated by the census, accounting for spatial clusters of population around schools, airports, hospitals, prisons, workplaces and leisure facilities. Smith and Fairburn (2008) attempted to account for some forms of visitor population that may be present within a destination, for example via incorporation of some forms of visitor accommodation (hotels, guest houses and some campsites and holiday parks). Only accommodation listed and clearly identifiable from the Ordnance Survey 'MasterMap - AddressLayer 2' product were incorporated and they noted two major obstacles. First, the address listings contained only a small proportion of the total accommodation stock that was

thought to exist; second, having identified specific sites, they suggested that "there is no obvious way of populating such features" (Smith and Fairburn, 2008, p51). Their experience in handling tourist populations within the NPD highlights that identifying the potential accommodation stock and populating that stock (based on some form of overall capacity and seasonal distribution) is a challenging and previously unaccomplished task. The handling of visitors and associated seasonal fluctuations within small area population geographies is a weakness identified in international contexts too. For example, Bhaduri (2008) notes the difficulties and challenges encountered in identifying daytime populations in the US, especially where these are made up of an influx of tourists or visitors with seasonal differences in numbers or distribution.

In spite of the obvious difficulties, Martin *et al.* (2009) note that there are clear arguments for understanding seasonal population movements resulting from tourism, citing a number of useful applications which range from hazard exposure (see for example Smith *et al.* (2013)), emergency service response (a useful example is provided by Ahola *et al.* (2007) through to service demand forecasting. In addressing this issue, however, Martin *et al.* (2010), p2 note that "a current area of deficiency is detailed counts for visitor numbers to residential and leisure facilities". Consequently, Cockings *et al.* (2010) claim that even relatively modest advances in the availability of data suitable for understanding spatial and temporal population fluctuations driven by tourism would represent advances in understanding small-area populations.

Section 3.4 considers further the need for data suitable for identifying small-area visitor numbers, their seasonal and spatial distribution and subsequent expenditure.

3.4 Understanding the local impacts of visitor expenditure

At a national or regional level, data collection relating to the domestic tourist sector (via the UKTS/GBTS) is well-developed and comprehensive (Beynon, Jones and Munday, 2009). However, analysis of the economic contribution of tourism to local economies and services is largely dependent on information about visitors and their spending, derived from national survey data. The relatively small sample sizes mean that these surveys cannot usually be disaggregated below regional (or at best county level) with confidence as to their robustness. Information on tourism at the local level is therefore reliant on local survey data which may often be outdated, inconsistent or based on very small samples. Nevertheless, most local authorities hold a database of visitor accommodation within their district and this can be used in conjunction with economic impact models to understand more about tourism at the local level, drawing on national survey data where appropriate. This section first considers data collection by local authorities before considering the economic impact models that can be used to identify characteristics of visitor spending at the local level.

3.4.1 Data collection at the local level

The ONS Tourism Intelligence Unit (TIU), formed in 2008, aims to make considerable improvements to tourism statistics at a national, regional and local level, recognising the inherent weaknesses in data collection, especially at the local level (Smith *et al.*, 2010). The ONS TIU have made recent advances in determining the economic impact of tourism to the regions and sub-regions of the UK, and within specific industries (Buccellato *et al.*, 2010b; TIU, 2011). The ONS TIU has produced a number of guidance notes to support local authorities in building local information on the economic impacts of tourism (such as 'measuring the supply side of tourism' (White, 2010a)). These guidance notes are designed to "provide a consistent framework with which to measure and collect data on various facets of the tourism industry" (White, 2010b, p3) and seek to promote a consistent, bottom-up approach. This undoubtedly represents an advance in the structure and guidance for the provision of a robust and timely local-level data infrastructure on tourism. Nevertheless, the majority of outputs produced by the TIU in its first five years relate to national or regional economic impacts, or to the development of a national tourism satellite account (TSA) (Buccellato *et al.*, 2010a; Buccellato *et al.*, 2010b).

Data on visitor numbers and their associated expenditure within specific counties, local authorities or destinations thus remain reliant on information derived from surveys commissioned by local authorities (and local destination management organisations). Whilst guidance exists, many of these organisations lack the budget or resources to frequently commission the full range of visitor surveys that would be useful in order to understand the local tourist sector (Middleton, 2002). This thesis relies on information from two organisations; South West Tourism (SWT) and VisitKent. Both organisations were well-resourced (with SWT having subsequently ceased operation) and had built up some form of local-level data collection. In part, it was the availability of data from these organisations that guided the choice of study areas for this thesis.

SWT was the organisation previously responsible for delivering the tourism strategy for South West England, including the county of Cornwall. SWT benefited from its own in-house research team, carrying out a range of local, destination-specific visitor surveys and a comprehensive audit of accommodation, all of which represent important local insight, which is drawn upon within this thesis to complement national and regional data. VisitKent benefit from funding as part of an EU funded SusTRIP (Sustainable Tourism Research and Intelligence Partnership) research programme[4]. This has allowed VisitKent to develop detailed local data collection and to commission bespoke research for the benefit of the industry as a whole. Some of this research considered traditionally under-researched sectors, such as VFR tourism, where findings from their research are discussed in section 3.5. Whilst

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[4] http://www.sustainabletourismresearch.eu/index/home

both these organisations could be considered to be industry leaders (in terms of their research and data collection), there remain a number of weaknesses and omissions in their data collection. As a result, a number of additional ad-hoc surveys and studies are relied upon within this thesis in order to 'plug the gaps' in the insight available from national or local data collection.

Nevertheless, the availability of local data means that both SWT and VisitKent were able to commission detailed analysis (via the Cambridge Model, outlined in section 3.4.2.2) to identify the economic value of tourism to their constituent counties (in the case of SWT) or Local Authority Districts (in the case of VisitKent). Such data has informed the modelling undertaken within this thesis, and section 3.4.2 considers the importance of economic impact assessment models in understanding tourism at a local level.

3.4.2   Economic impact assessment models

Large scale, national sample surveys, such as the IPS, GBTS and GBDVS provide reliable and timely data about national and regional visits. Results are up-scaled prior to publication in order to be representative of the population as a whole, and a number of inferences can be drawn about the nature of tourism at a national or regional level. In particular, they provide robust and consistent information on visitors and their associated expenditure, yet they do not generate reliable data at the local level (Beatty *et al.*, 2010). Nevertheless, these national surveys (in particular the UKTS/GBTS) are drawn upon throughout this thesis and used in conjunction with other survey data as a tool to understand more about visitor numbers, their seasonal and spatial distribution and associated expenditure.

In conjunction with these surveys, a number of expenditure modelling techniques are used to translate survey data into estimates of local level visitor spend and its impacts. Frechtling (2006) explains that economic impact models generally ascertain overall levels of tourist expenditure, applying some form of multiplier rate in order to quantify the direct and indirect impacts of this expenditure at a sub-regional level. White (2010b), in his guidance notes to local tourist officials, acknowledges that two such branded models exist in the UK, both recognised by the Department for Communities and Local Government (2006). These are the 'Cambridge Local Impact Model' (Cambridge Model) and the 'Scarborough Tourism Economic Activity Monitor' (STEAM). Both models are spreadsheet-based and have been developed commercially for application across the tourist industry, via licensing agreements with regional tourist boards and consultancy organisations. Recognising that there is limited information available on the volume and value of tourism at the local level, these models aim to generate an assessment of local economic impacts by making use of limited local-level data that may be available, complemented with data from regional or national surveys (Middleton, 2002).

3.4.2.1 Scarborough Tourism Economic Activity Monitor

The STEAM model (first implemented in the Yorkshire (UK) coastal resort of Scarborough in 1989) is primarily a supply side model and is owned and managed by Global Tourism Solutions (UK) Ltd. The model, its methodology, equations and expenditure/multiplier rates are commercially sensitive and not made available to end users (neither has the model been the focus of any academic study reported within the literature). As such, details of the model itself are sketchy and reliant on inferences that can be drawn from local-level reports detailing outputs from the model (e.g. GTS (2009)), and a slightly dated review article carried out on behalf of the Local Government Association (Middleton (2002).

STEAM adopts a 'bottom-up' approach, estimating visitor expenditure based on key supply side indicators of tourism which are routinely available within a destination. These include information on the accommodation stock or on visitor numbers, inferred from visitor inquires at tourist information centres and recorded at specific attractions and large events. The accommodation stock is obtained from published sources (such as accommodation guides) and the number of bedspaces is used in conjunction with occupancy rates to determine levels of tourist activity (Middleton, 2002). Visitor expenditure is estimated for visits utilising a range of different accommodation types and visit purposes, broadly segmented as overnight visits (utilising serviced and non-serviced accommodation) alongside VFR trips and day visits (GTS, 2009). Thus, the STEAM model recognises the importance of accommodation in driving characteristics of visitor expenditure, using pre-determined expenditure and multiplier rates and estimating visitor expenditure in certain key categories such as accommodation and shopping.

3.4.2.2 Cambridge Local Impact Model

The Cambridge Model was launched in 1995 by Geoff Broom Associates, drawing on considerable experience working with UK regional tourist boards. The methodology employed by the model is consistent, well-regarded and understood within the industry, and can be applied at a range of spatial scales (South West Tourism, 2010b; TSE Research, 2012). The model was independently assessed and validated prior to launch (Vaughan, 1994) and the following outline of the model is based upon Vaughan's independent assessment (Vaughan, 1994), discussion between Vaughan and the author in 2011, and reports produced by South West Tourism (2010d) and TSE Research (2012).

The Cambridge Model estimates the volume and value of tourism and its associated direct and indirect (via multiplier effects) impacts within a local area. In contrast to STEAM, the approach taken is 'top-down', considering primarily the demand side. Existing survey data from the GBTS and IPS (plus other regional and national survey data) is used to estimate the volume and value of local tourism activity. Disaggregation to a county and local authority district level is based on a series of 'drivers', and these indicate the distribution of tourist activity (principally based on the accommodation stock) but also incorporating recorded

visitor numbers at attractions and information on employment in the tourist sector. Essentially, therefore, the model identifies the overall number of visits (by accommodation type) and their associated expenditure from the GBTS and IPS and distributes those visits to a county or local authority district level based on the accommodation stock.

The expenditure estimates produced by the Cambridge Model are not just based on commercial accommodation. They incorporate expenditure associated with second homes and with households hosting visiting friends and relatives, recognising that these are an important driver of visitor demand. However, the exact methodology for calculating the number of visits associated with these forms of tourism, or their distribution, is unknown. Nevertheless, the model is able to estimate visitor expenditure, at the local authority level, in five spending categories (accommodation, shopping for gifts, clothes and other goods, eating and drinking in restaurants, cafes and inns, entry to attractions and transport and travel costs). Multipliers are then applied to estimate indirect impacts on suppliers and local employment.

Vaughan's (1994) independent assessment and validation of the model identifies that its key strength is that the sub-regional estimates are based on (and constrained by) regional estimates of trips and their associated expenditure. However, in 2002, an enhanced version of the model was launched, incorporating a number of developments at the request of the South West Regional Development Agency (SWRDA). These improvements incorporated greater use of local data within the model, especially the use of accommodation occupancy rates (in conjunction with accommodation stock) as a determinant of sub-regional trip distribution.

3.4.3 Local survey data

The use of STEAM and the Cambridge Model as tools to understand the local impact of tourism are not usually considered within the academic literature and have had little impact outside the tourist sector. GTS (2009) clearly identify that commercial models such as STEAM are not made available to academic users. Nevertheless, the visitor surveys outlined in section 3.4, and insight gained from the economic impact models explored in this section, are used throughout this thesis to inform the development of small-area expenditure estimates. Chapters 6 and 8 directly utilise expenditure estimates obtained from Cambridge Model outputs, available at the County level for Cornwall and district level for Kent.

However, the Cambridge Model lacks any form of seasonal breakdown in its reporting of trip volumes or their associated expenditure. Whilst seasonal variations in visitor numbers are taken into account in producing expenditure estimates in each of these models, they are not explicit within the outputs and, as such, outputs cannot be used to identify seasonal variations in local-economic impact driven by tourism. A further weakness of these models (and of the majority of visitor survey data) remains the lack of distinction between different

types of food and drink expenditure, such that expenditure in grocery stores cannot be identified, as acknowledged by Stynes and White (2006).

Nonetheless, the review of these approaches has highlighted a number of important considerations that should be taken into account when estimating local visitor expenditure. Both the Cambridge Model and STEAM base their analysis principally on the volume of tourism. As such, they recognise that the overall number of visitors has an important impact on the expenditure at the destination. In understanding visitor expenditure at the local-level, an understanding of the volume and seasonal distribution of visitors is therefore required at the smallest possible spatial scale. As noted in section 3.3, this represents an under-researched and under-reported component within small-area population estimates and, since no specific data source exists, small area visitor numbers and their associated spatial distribution will need to be estimated as part of this thesis.

Secondly, in both models, visitor accommodation plays a crucial role. In the case of STEAM it is a fundamental building block upon which estimates are based, whilst in the Cambridge Model it is used to distribute visits to lower-level geographies. In both models, accommodation occupancy rates are also applied to determine seasonal patterns of accommodation utilisation, although the results are not reported with any form of seasonal breakdown, which remains a weakness in these model outputs. It is thus recognised that the exact value of visitor expenditure, and its seasonal distribution, will be driven by the accommodation used (or the type of visit where no accommodation component exists) as explored further in section 3.5.

3.5   Accommodation as a key driver of seasonal and spatial patterns of visitor expenditure

Accommodation is one of the key components of the tourist supply side (Pearce, 1989). Accommodation impacts on food and drink consumption habits (as outlined in this section and explored further in Chapter 5) and, between them, visitor accommodation and food and drink have been found to represent over 50% of UK tourist consumption (by share of expenditure) (Bryan *et al.*, 2006). This section briefly considers the range of accommodation provision available within tourist resorts. The seasonal and spatial patterns inherent in utilisation patterns for each form of accommodation are illustrated. Commercial accommodation is considered first (section 3.5.1), followed by other forms of accommodation (section 3.5.2). The discussion seeks to consider the grocery consumption associated with different forms of accommodation.

Insight is drawn from the academic literature and industry data (largely derived from local small-scale surveys). The focus of this section is almost exclusively concerned with the seasonal and spatial distribution of tourist activity by domestic overnight visitors, as it is these visitors that have a major role in generating grocery expenditure within the resorts and

destinations explored in Chapters 4 - 8. Figure 3.5 illustrates the type of accommodation used (by broad category) for domestic trips within England. The data is drawn from the UKTS and is displayed by region. It reveals that almost 45% of all self-catered trips are to South West England, whilst only 1% of self-catering trips are to London. The South West also accounts for over 35% of all camping and caravanning trips (which have been considered separately to other forms of self-catering). These forms of accommodation are reported to generate considerable grocery expenditure among visitors (Timothy, 2005). The importance of the South West as a destination for domestic tourism is clearly highlighted by Figure 3.5 and Cornwall, which forms part of the South West region, is the main focus of the modelling that follows.
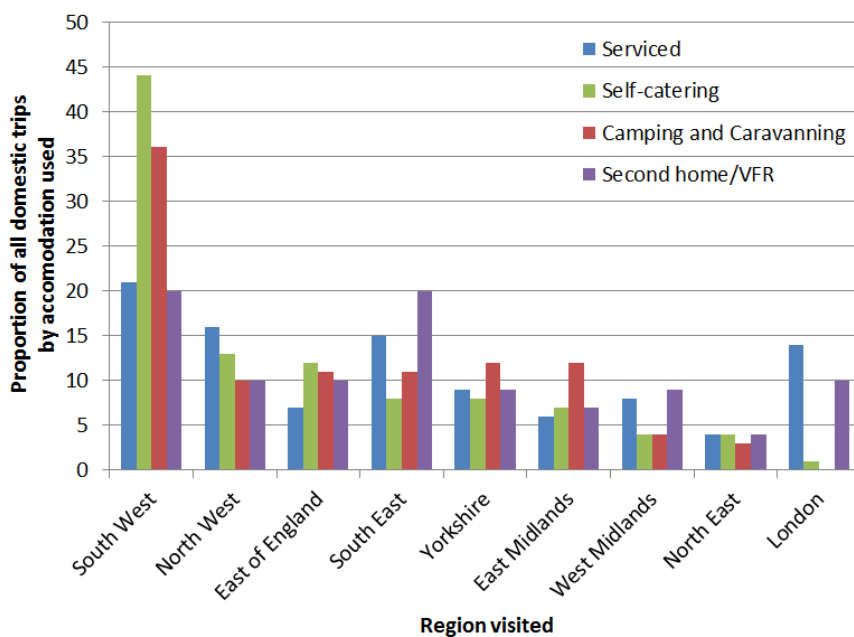
Figure 3.5 - Accommodation used by region visited

'Self-catering' includes all forms of self-catering accommodation with the exception of camping and caravanning (touring), shown separately. Source: UKTS (2010) extracted via online data browser: http://dservuk.tns-global.com

This brief review of visitor grocery expenditure does not seek to consider all the factors that may affect visitors overall spend within a destination. There are a complex range of interrelated factors that are a product of the visitors themselves, the characteristics of their visit, characteristics of the destination itself and the expenditure categories considered. For a very comprehensive overview of an exhaustive range of factors influencing visitor expenditure (ranging from marital status to language) see Kruger *et al.* (2012) who provide a succinct overview and signposting to over 50 additional studies which focus in particular on those individual factors.

Each form of accommodation is considered in turn, beginning with commercial accommodation, and specifically serviced accommodation.

3.5.1   Commercial accommodation

3.5.1.1   Serviced accommodation

Commercial accommodation is itself subcategorised based on the level of service provided, with serviced accommodation (such as a hotel or guest house) providing some form of catering for guests. There are a diverse range of serviced accommodation options and providers within any destination, ranging from international chains through to independent small-scale operators. Large chains have been increasingly innovative in developing accommodation to meet the diverse needs of visitors, from business executives to budget travellers, and use marketing, special offers and third party booking agencies to maintain high occupancy rates all year round. In contrast, smaller guest houses and bed and breakfast accommodation may be far less commercialised (especially in rural and coastal areas), often providing a limited number of rooms or bedspaces with very basic facilities for guests.

Serviced accommodation almost always provides the option of breakfast for guests and may also provide evening meals or lunches. These establishments generally provide no catering facilities accessible for guests to prepare their own food. Consequently, grocery expenditure by these guests is thought to be minimal. Nonetheless, owners and operators of these establishments may purchase items for guest consumption (such as breakfast ingredients) in local grocery stores. This form of expenditure represents visitor-induced spend. It is not acknowledged within the academic literature, but is considered further in this thesis via primary data collection carried out by VisitKent on behalf of the author (see Chapters 5 and 8). Consequently, an understanding of the distribution and seasonal characteristics of this form of accommodation is important for subsequent modelling.

Some forms of local-level data collection in this sector are strong owing to an EU directive which requires national tourist boards to monitor occupancy levels. Accommodation occupancy data are an important tool to assess the performance of the commercial accommodation sector at a local or regional level, often used to benchmark against similar destinations (White, 2010a). As part of an EU directive on tourism statistics (introduced in 1995) (EU, 1995), the UK national tourist boards, including VisitEngland, must report serviced accommodation occupancy rates to Eurostat. This is usually achieved through a sample of accommodation operators who self-report their occupancy rates (rooms and bedspaces occupied as a proportion of their total stock) on a monthly basis. These operators are usually recruited locally by local authorities or destination management organisations, who collate occupancy rates from their local accommodation operators and submit them to VisitEngland, where they form part of the national occupancy survey. In their guidance notes to tourism officials operating at the local level, the ONS TIU (White, 2010a), for example, provides clear guidance on how to set-up and administer an occupancy survey, including weighting of results to ensure that the reported rates are representative of the serviced accommodation stock as a whole.

As noted fully in Chapter 8 (with reference to Kent), online systems such as RIBOS[5] (ReZolve Internet-Based Occupancy Software) provide a simple web-based interface for accommodation operators to supply occupancy rates. In the case of Kent, this system offers cash prizes to respondents, and participants are able to benchmark their performance against similar operators in their local area. This encourages participation and maintains high response rates. This form of data provides a valuable indicator of the performance of aspects of the tourist sector locally. The serviced accommodation stock in Cornwall and East Kent are outlined in Chapters 5 and 8, where occupancy rates and expenditure rates are used to generate seasonal estimates of induced visitor spend. This chapter now turns attention to self-catered accommodation.

3.5.1.2 Self-catered accommodation

Self-catered accommodation is defined as "the exclusive use of self-contained accommodation which is available for commercial letting to the public for a fixed period of time, is open for published periods of letting and is let un-serviced i.e. without a supply of prepared food, but must have access to facilities for the letting party to store and prepare food on the premises" (Lynch *et al.*, 2003, p4). By definition therefore, self-catering accommodation provides catering facilities for occupants to prepare their own food and drink. The importance of self-catering accommodation should not be underestimated, with research by VisitEngland suggesting that this sector is set to experience considerable growth in visitor numbers. This sector currently accounts for almost 60% of all leisure trips (in terms of 'bed nights'), with 37% of these taken during July and August (VisitEngland, 2011), undoubtedly driven by the importance of the growing (but highly seasonal) family holiday market to this sector (Thomason and Keeling, 2012).

Johns and Lynch (2007) carried out a comprehensive review of self-catering accommodation in a UK context, highlighting the full range of accommodation formats and providers that exist within this sector. They also note that this sector has traditionally been neglected by academic research, which they consider to be 'astonishing' given the importance of this sector, both in terms of the number and range of accommodation units it provides, and its contribution to local economies. The self-catering accommodation sector is vast and includes a broad range of accommodation. This incorporates cottages and apartments, chalets, bunkhouses and time-share units, alongside static caravans and camping or caravanning pitches. Accommodation may represent individual dwellings (drawn from the residential housing stock) or conversion of outbuildings on farms or similar properties (Walford, 2001).

This sector also comprises purpose built units located on holiday parks, offering chalet, lodge or camping accommodation alongside entertainment and leisure facilities. Brookman (2009) and Mintel (2011b) identify that many of the large holiday parks operated by

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[5] http://eos.ribos.co.uk/

companies such as Bourne Leisure (Butlins and Haven), Park Resorts and Centre Parks, have enjoyed a recent period of growth. This is especially true among the family market, with significant investment and improved facilities at these sites, which, according to Johns and Lynch (2007), are almost exclusively located close to major coastal resorts (such as those shown on Figure 3.4).

Given the broad range of accommodation within this sector, it is inevitable that seasonal and spatial patterns are complex. The self-catering sector is highly seasonal in nature, particularly where accommodation relies on favourable weather conditions (e.g. camping and caravanning) or appeals to the family market (many holiday parks), exhibiting a season generally running from Easter to late October, and peaking in August. The seasonal distribution of (domestic) trips by accommodation type is shown on Figure 3.6 and is drawn from the UKTS. Camping and caravanning is shown separately to other forms of self-catering accommodation as the seasonal distribution of these visits tends to be pronounced. Self-catering accommodation, and in particular camping and caravanning, exhibit a very pronounced seasonal pattern with almost a quarter of all camping and caravanning trips beginning during August (with a further 23% in July). This period coincides with the school summer break and usually represents some of the most favourable weather conditions for these activities. Other forms of self-catering accommodation exhibit a similar seasonal distribution, whereas serviced accommodation and the use of second homes or trips staying with friends and relatives, show a far more uniform seasonal distribution.
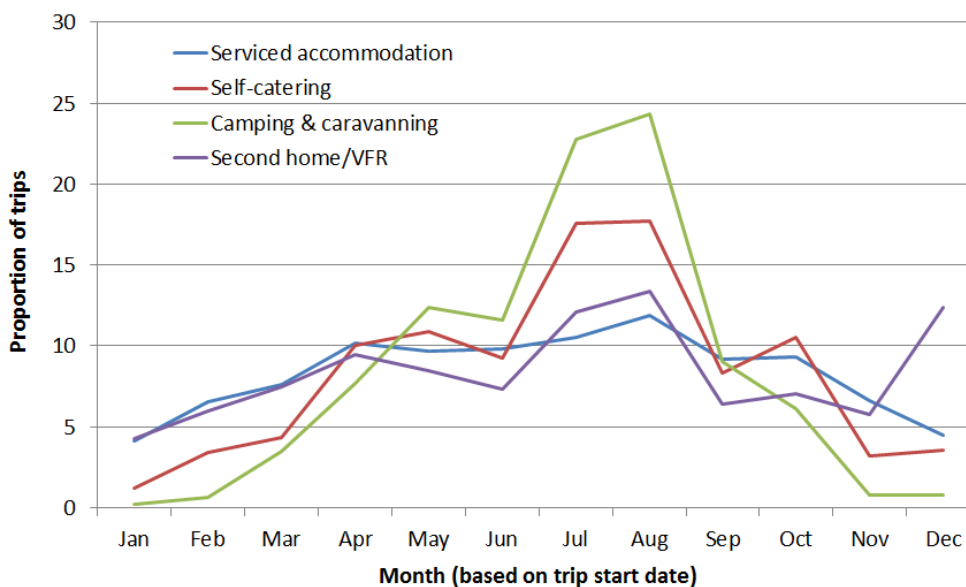
Figure 3.6 - Seasonal trip distribution (all domestic trips) based on accommodation type

Self-catering includes all forms of self-catering accommodation with the exception of camping and caravanning, shown separately. Source: UKTS (2010) extracted via online data browser: http://dservuk.tns-global.com/

As outlined fully in Chapters 5 and 8 (with reference to Kent and Cornwall), some forms of self-catered accommodation (such as accommodation located on holiday parks) tend to exhibit a high degree of spatial clustering. This results from the concentration of a large number of accommodation units on large sites alongside provision of visitor facilities (such as entertainment and swimming pools). Not only does this produce considerable spatial clusters of visitors and their associated demand, these may be highly seasonal, driven not only by the school calendar and national holidays, but also by the operating season at these establishments.

Whilst the seasonal and spatial patterns evident within self-catering accommodation usage are pronounced, obtaining data on the self-catering sector is more complex. The vastly fragmented range of accommodation options and ownership present in this sector makes it difficult to obtain comprehensive data on the accommodation stock or its utilisation. In a review of self-catering accommodation in Yorkshire (UK), Thomas and Hind (2007) identified that small-scale operators generally had very poor engagement with their regional tourist boards, noting difficulties encountered by the local tourist board in establishing the provision of self-catered accommodation within their region. As such, ascertaining the potential stock of self-catered accommodation within a given area, or its seasonal occupancy (self-catered accommodation is not part of the national occupancy survey), presents a number of challenges, as outlined in Chapter 5. Nevertheless, the importance of this sector in generating seasonal and spatial clusters of visitor expenditure is such that it is crucial to build a demand-side understanding of expenditure associated with these visitors.

All forms of self-catering accommodation are likely to generate additional visitor spend on food and drink purchased outside their accommodation (Dudding and Ryan, 2000; Timothy, 2005). By definition, this sector provides guests with the opportunity to purchase and prepare their own food. Whilst many occupants of self-catered accommodation will still exhibit a propensity to eat out, a key selling-point of this sector is that visitors can be flexible and cook and eat whenever it suits them (Thomason and Keeling, 2012). For example, in a study of visitors in County Wexford, Ireland, Mottiar (2006) identifies that visitors staying in a rented cottage or apartment were found to spend an average of €24.24 per day (per party) on groceries. This clearly highlights that guests with access to catering facilities exhibit a tendency to make use of those facilities, thus generating grocery spend.

In a study of visitors to Queensland, Australia, Stoeckl et al. (2006) identify that different types of party show a different propensity to visit grocery stores, to eat out, or to cook their own meals whilst away from home, as summarised in Table 3.2. Their findings clearly demonstrate that there is a large variation between different group's food and drink consumption habits, with retired couples being over twice as likely to cook their own meal compared with a single traveller. Retired visitors to Queensland are also far more likely to visit grocery stores frequently (around once every two days), compared to other parties. It is

thus important, where possible, to consider the impact of accommodation type and party type or purpose of visit when attempting to understand the nature of visitor grocery consumption.

Whilst the impact of accommodation and party type on grocery spend is acknowledged by these two academic studies, they provide limited evidence and note an almost complete absence of further studies within the literature that consider the grocery consumption habits associated with visitors in the self-catering sector. Whilst the academic literature reveals few specific insights into the actual value of visitor expenditure in grocery stores, this form of consumption is increasingly recognised by the industry itself.

Some forms of accommodation provision are recognised by trade associations (such as the British Holiday and Home Parks Association (BH&HPA) (representing British Holiday park operators). Larger operators such as the Camping and Caravanning Club (CCC) also have established PR departments who represent the interests of themselves and similar operators across the industry. Both the BH&HPA and the CCC are effective at communicating the positive benefits that their parks and sites may bring to local communities, recognising that the full value generated by these sites (at a local level) may often be underestimated or overlooked.

Table 3.2 - Propensity to use grocery stores and cook own meals based on visitor type

Type of Party	Grocery shop (times per day)	Cook own meal (times per day)
Retired couple	0.54	0.86
Family no children	0.44	0.76
Couple	0.38	0.71
Group of friends/relatives	0.30	0.70
Family with children	0.27	0.66
Retired single	0.53	0.74
Single	0.19	0.33

Source: Adapted from (Stoeckl *et al.*, 2006, p105)

The CCC is a membership organisation operating 100 sites across the UK for tourers with tents, trailer tents, caravans or campervans (motor-caravan). In 2007 the CCC carried out a visitor survey which aimed to identify the contribution of CCC visitors to the local economy across all their UK sites (covering coast, countryside and urban areas) and reflecting their full membership base. Although the type of visitor to CCC operated sites may differ from some of the smaller, independent sites, the CCC does publish a bi-annual directory of touring sites which lists over 4,000 sites in the UK (Eastlake, 2008), suggesting that CCC members

stay at a range of sites across the UK not operated by the CCC, no doubt exhibiting similar consumption habits (where local facilities are available).

Carried out during the summer, the survey (760 respondents) identified that (with the exception of site fees themselves) the highest spend within the destination was reported to be on supermarket provisions, closely followed by expenditure on other sources of food and drink, including eating in local pubs and restaurants. The survey found that the average spend on groceries was £66.08 per pitch per week (accounting for average length of stay among respondents). The survey identified key differences in grocery spend by type of unit, with tent campers tending to spend more on groceries (£93.66 per pitch per week) than those using a motorhome (£36.75 per pitch per week), perhaps suggesting that the latter have more space and facilities to store food brought from home. The type of party was also seen to have an influence on expenditure, with families (those with children) spending around 25% more than those without (even after accounting for party size).

The British Holiday and Home Parks Association (BH&HPA) have also carried out a series of studies to demonstrate the positive economic impact of these parks on local economies (see for example BH&HPA (2011) and BH&HPA (2012)). In a face-to-face survey of 517 visitors to 21 holiday parks, visitors were found to spend an average of £98 per trip (equating to £79.76) per week on 'food and drink for self-catering purchased off-park' (therefore excluding purchases from an on-site convenience store). This represents around a quarter of respondents total trip-related spend, recognising the importance of food and drink as a driver of expenditure among visitors using self-catered accommodation (BH&HPA, 2012).

It is clear therefore that self-catering accommodation drives visitor grocery expenditure and that whilst this is an under-researched area, this form of consumption must be considered within subsequent modelling. The studies and surveys identified above are utilised in Chapters 5 and 8 to build small-area seasonal demand estimates. This chapter now turns attention to non-commercial accommodation, including the use of second homes and trips hosted by friends or relatives.

3.5.2   Other forms of overnight accommodation

Alongside commercial accommodation, visitors also often stay with friends and relatives, or within a second home that they own. These visitors may exhibit very different holidaymaking behaviours than other forms of visitor as they have a lower outlay on accommodation. Nonetheless, visits associated with these forms of accommodation bring considerable benefits to the local economy. Households may face considerable additional costs in hosting visitors, and second home owners have financial obligations towards their second home, generating additional local expenditure (Spindt and Weiss, 2009; WTO and ETC, 2007). Mottiar (2006) examines the expenditure patterns of second home owners in County Wexford, Ireland, and notes, for example, that second home ownership generates considerable expenditure within the destination on both grocery shopping and DIY. The

following sub-sections briefly outline the nature of second home ownership and of visits to friends and relatives as a form of accommodation utilised by visitors and as a driver of expenditure.

3.5.2.1 Visits hosted by friends and relatives

The visits to friends and relatives (VFR) market includes trips (both day and overnight) where the primary motivation, and thus main purpose of the trip, is to visit friends or relatives. Visitors may also visit friends and relatives whilst on a holiday or business trip without this visit being the main trip motivation. A comprehensive study of VFR tourism carried out for VisitKent suggests that the VFR market is set to grow in importance due to a complex range of factors, including an ageing population, growth in the number of students (who are a major driver of VFR visits, as outlined by Bischoff and Koenig-Lewis (2007)), a rise in single person households and increased mobility (The Tourism Company, 2011). As a major category of inbound and domestic tourism (and also as a category of accommodation used by visitors on all forms of trip) data is routinely collected on trip volumes and expenditure associated with VFR tourism via the GBTS and IPS. Figure 3.3 above outlined the distribution of VFR trips (where VFR has been reported as the trip purpose). As noted in section 3.2.1, these trips show a less pronounced seasonal distribution than trips for other purposes, with less concentration around the peak period. Thus whilst these visits may not contribute considerably to the peak season demand uplift experienced around stores in coastal resorts, they are likely to generate more sustained demand uplift throughout the year.

It must be noted that not all visitors who report a trip purpose of 'visiting friends and relatives' will actually stay in the home of their hosts. For example, in 2010, the UKTS reveals that the South West attracted over 24m VFR nights (driven by domestic tourism), of which only 84% involved an overnight stay in the hosts' home. The remaining 16% of visitor nights on trips whose main purpose is VFR are accounted for by other forms of commercial accommodation, with visitors demonstrating a preference for staying independently, away from their hosts, in order to gain privacy and independence (and to reduce the burden on their hosts) (Bowen and Clarke, 2009). Even where visitors do not stay with their hosts, the role of hosts in providing food and drink for their guests should not be underestimated. In a comprehensive survey of VFR hosts, followed up by a series of focus groups, The Tourism Company (2011) identify that entertainment at home (which includes dining in) was an important 'activity' in a considerable proportion of visits. Seaton and Palmer (1997) argued that VFR tourism has always been 'marginalised' as its assumed value was small. The limited evidence available (Bischoff and Koenig-Lewis, 2007; ETC, 2002; The Tourism Company, 2011) suggests that this is not the case.

Expenditure associated with visitors who are hosted by friends and relatives is often overlooked, especially within official statistics (ETC, 2002). Whilst these visitors may spend little on food and drink, hosts may face considerable costs in providing food and drink for

visitors. Backer (2007) suggests that among all the additional costs faced by hosts (which commonly include fuel, admissions to attractions, restaurants/cafes and entertainment), the greatest additional expense is on groceries, with over 80% of VFR hosts reporting that they purchase additional food and drink to meet the needs of their guests (Briggs, 2002). It is important to ensure that this form of expenditure is incorporated in demand side estimates of visitor-induced grocery demand, since the literature suggests that additional grocery purchases account for 26% of a host's total additional expenditure (ETC, 2002). Whilst the Kent study, based on over 1,200 responses, did not specifically consider hosts' grocery spend, it did identify that hosts spent an average of £141 per visit (incorporating spend on eating out, visiting attractions etc.), highlighting the value, more generally, of these forms of visit to local economies, and considered further in Chapters 5 and 8.

3.5.2.2 Second homes

A 'second home', also sometimes termed 'holiday home', reflects the usage of houses or other dwellings, whereby owners use the dwelling for holiday purposes in conjunction with a permanent residence (Hall and Müller, 2004). The 2011 census[6] noted that 2.8% of usual residents in England and Wales had a second address that they used regularly (more than 30 days a year). The English Housing Survey, an annual sample survey of around 17,000 homes, (which replaced the Survey of English Housing), identified that 50% of second home owners claimed that they use their secondary dwelling as a holiday home rather than simply as an investment, previous residence or students' term time address (Communities and Local Government, 2011). Whilst these dwellings are recorded within the census, and also identifiable via council tax data (Wyatt, 2008), they are not recorded as a uniquely identifiable subset of the accommodation stock within national surveys.

Where second homes are used as a holiday home, they tend to generate localised seasonal expenditure when occupied. Muller (2004) notes that some second homes may be used virtually every weekend, becoming an integral part of their owners' regular routine (whereas others may be used only seasonally or for isolated visits). However, many second home owners also choose to rent-out their dwelling when unoccupied, especially during the peak season. As such, this form of accommodation may also be regarded as part of the self-catering accommodation stock, generating additional local expenditure. However, if rented for more than 140 days per year the dwelling may be registered as a business and thus not appear within housing statistics (South Lakeland District Council *et al.*, Undated). As such, identifying the stock of second home units and making inferences about utilisation patterns or the actual expenditure associated with these dwellings is tricky.

In terms of expenditure, a set of recent qualitative studies in Ireland (where a small number of localised studies have considerably added to the research base on second home tourism)

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[6] Table QS106EW

interviewed second home owners and identified a range of approaches to the provision of groceries, including those who tend to bring most food from home, stating that "fresh food down here wouldn't be as good as what you'd get, say in Tesco, just the variety, so I would tend to shop before I came down and bring a lot of fresh food with me" (Quinn, 2010, p198). Others typically shop within the vicinity of their second home claiming "...we would tend to bring down some food to keep us going for a day or two. But they have a shop here and it stocks everything, and then over in Wellington Bridge there's a bigger supermarket" (Quinn, 2010, p166).

Furthermore, many second home owners are likely to keep their home stocked with everyday items and therefore will not be required to purchase these from scratch on each trip, which may be the case for those renting accommodation. Quinn's findings support those of another qualitative study, considering visitors to County Wexford, Ireland. Here, Mottiar (2006) noted that almost 60% of second home owners reported that they regularly purchase groceries in the local supermarket. Consequently, evidence suggests that second home ownership generates grocery expenditure within a destination, yet very little is known about the actual value, volume or seasonal pattern of this form of expenditure, as addressed further in chapter 5.

This chapter has outlined the range of accommodation (both commercial and non-commercial) found within a destination. Reference to the literature and industry sources reveals evidence that all forms of accommodation generate some form of local grocery spend within the destination. Whilst some data sources have been identified (and are explored further in Chapter 5), it remains clear that relatively little is known about the seasonal patterns of grocery expenditure associated with these forms of accommodation at a local level as outlined in section 3.6.

3.6   Conclusion

This chapter sought to situate and contextualise this thesis within the tourist sector, identifying the role of visitors in driving local seasonal demand uplift within grocery stores. Section 3.2 introduced tourism as a demand side concept, recognising the importance of domestic holidaymakers in driving a highly seasonal and spatial distribution of trips, particularly within coastal resorts. Section 3.3 outlined a series of key national surveys which provide detailed and timely information on the tourist sector, but noted the lack of data collection at the local level. As such, it is acknowledged that very little is known about the volume or seasonal distribution of visitor expenditure at the local level, and even less can be inferred about the localised impacts on specific services such as grocery stores.

Nevertheless, a series of economic impact models are commonly applied within the tourist sector. These attempt to estimate sub-regional visitor numbers and associated spend and highlight a number of important considerations. These must be addressed when building

seasonal and spatial estimates of small area visitor populations and their associated spend. In particular they note the role of visitor accommodation in driving the spatial and seasonal distribution of visitor spend, which was explored, based on a handful of industry and academic studies in section 3.5. This chapter identifies a number of data sources and modelling tools for exploring tourist consumption, but concludes that very little is known about seasonal and spatial patterns of visitor grocery expenditure at the small-area level.

Using observations from the grocery industry, Chapter 2 identified that grocery stores in popular tourist resorts (especially those in coastal areas) exhibit pronounced seasonal demand uplift. The seasonal nature of visitor demand identified in this chapter, and the high propensity for certain types of visitor to purchase groceries, supports the notion that visitors are driving the demand uplift experienced around stores in tourist resorts. This is explored further in Chapter 4, making use of consumer loyalty card data from the Nectar scheme, allowing consumption by visitors to be identified. Much of the insight outlined in this chapter is applied further in developing small-area seasonal and spatial expenditure estimates in Chapters 5 and 8.

Chapter 4: Visitor grocery expenditure in Cornwall - analysis of store and loyalty card data

4.1 Introduction

Chapter 3 identified that the UK tourism sector is experiencing a period of growth, with increasing numbers of domestic holidaymakers enjoying breaks within the UK. Self-catered accommodation in the form of rented cottages, apartments, static caravans, lodges and camping and caravanning have enjoyed much of this growth in visitor numbers (Johns and Lynch, 2007). These forms of accommodation generate visitor expenditure on food and drink which is purchased from a variety of sources including supermarkets and other grocery stores (Dudding and Ryan, 2000). This type of consumption is often neglected within the tourism literature and retail modelling, yet retailers note that visitor demand may make up a considerable proportion of store-level trade in certain destinations (see Chapter 2). Chapter 3 has identified that tourist resorts in South West England are important destinations for domestic tourism, and a number of resorts in the county of Cornwall, South West England, form the basis for this chapter and for subsequent modelling. Section 4.2 briefly introduces the county of Cornwall, with specific resorts introduced further throughout the discussion that follows and in subsequent Chapters.

The aims of this chapter are threefold. First, and building on the discussion from Chapter 2, section 4.3 seeks to identify the store-level impact of seasonal sales fluctuations, using trading data obtained from Sainsbury's stores in Cornwall, including stores in the popular Cornish coastal resorts of Newquay and Bude. Having identified that store-level seasonal sales uplift is evident, this chapter secondly seeks to demonstrate that this uplift is attributable to expenditure inflow driven by visitors. Consumer level loyalty card data is used and allows consumers' characteristics, including their residential origin, to be identified. Finally, this loyalty card data is used in order to understand the nature of visitor demand, considering actual consumer expenditure attributable to visitors whilst away from home and drawing comparisons with local resident spend in the same stores (and with visitors usual home consumption habits).

The majority of studies of visitor spend (or indeed of visitor characteristics more generally) take place at the aggregate level (considering all forms of expenditure) for example Craggs and Schofield (2009). Other studies consider only a subset of visitors (i.e. Downward and Lumsdon (2000) who consider visitors within only one destination, or Algere and Magdalena (2010) who consider only repeat visitors) or focus explicitly on visitor spend associated with particular short term events (e.g. Barquet *et al.*, 2011; Bracalente *et al.*, 2011; Young *et al.*, 2010). Spending categories such as 'food and drink' are used frequently within destination specific visitor surveys (often referred to as 'destination benchmarking'), yet are

predominantly concerned with eating out, such that spending on food and drink purchased from grocery stores is not uniquely identifiable. There are consequently very few studies that explicitly consider destination level spend on individual expenditure categories such as groceries, to which this chapter makes a contribution.

The use of customer loyalty card data from the Nectar scheme affords a unique opportunity for analysis. Chapter 2 identified that there are around 12 million active Nectar cards in use at Sainsbury's stores, representing a valuable dataset to understand consumer level purchasing. This form of data is not usually made available for academic investigations and allows visitors and their associated expenditure to be inferred (based on their loyalty card being registered to an address outside the store catchment). Using loyalty card data allows customer level visitor spend to be identified without the need for surveys, and gives an insight into the characteristics of consumer demand, as observed on the supply side.

Section 4.2 introduces Cornwall as a popular destination for highly seasonal domestic tourism, with tourism concentrated on a series of major resorts, explored further in this chapter and subsequent modelling. Section 4.3 introduces the study stores and store-level trading data that has been made available for this thesis and uses this data to identify store-level seasonal sales variations, which are also broken down by product category. Sections 4.4 and 4.5 explore seasonal trade at four study stores using loyalty card data. Specifically, visitor spend is identified and comparisons are drawn with local resident expenditure and visitors' usual home consumption. This is an important step in unpicking some of the characteristics of visitors and their associated expenditure and is used to inform the modelling approach developed in Chapters 5 and 6.

4.2 Cornwall

Cornwall forms the study area for this chapter, and for subsequent demand estimation, model development, calibration and scenario evaluation (Chapters 5 - 7). Cornwall represents a coastal peninsula in south west England (Figure 4.1). According to analysis by the ONS TIU, the South West region displays one of the highest shares of tourism activity in the UK, with total tourist expenditure of £7.6bn, including £3.3bn from domestic overnight visitors, and another £3.1bn from day visitors (in 2008) (Buccellato *et al.*, 2010b). The South West represents one of the most popular destinations in the UK for domestic tourism and "A large part of the commercial landscape in the South West is concerned with, and devoted to, satisfying the needs of the visitors as consumers" (South West Tourism, 2010b, p10).

Cornwall is thought to attract around 25% of all tourist expenditure in the South West (South West Tourism, 2010d), and was awarded 'top UK holiday destination' in the 2010 British Travel Awards, also winning awards for 'Best UK Seaside Town' (St Ives), along with 'Best UK Day out Experience' for the Eden Project (VisitCornwall, 2010). Although geographically remote, it is Cornwall's location, landscape and distinctive regional identity

(Everett and Aitchison, 2008) that attract tourists, with established coastal resorts such as Newquay, Bude, Padstow and St Ives as important destinations. Traditional family beach holidays make up 28% of the market, whilst holidays focused on history and heritage are also important (South West Tourism, 2005a). St Austell is home to the Eden project, one of the top 20 UK major paid attractions (South West Tourism, 2010b), which alone attracted 1.1m visitors in 2008 (South West Tourism, 2010a), and is said to have generated £462m revenue within the local economy in its first five years of operation (HIL, 2005).
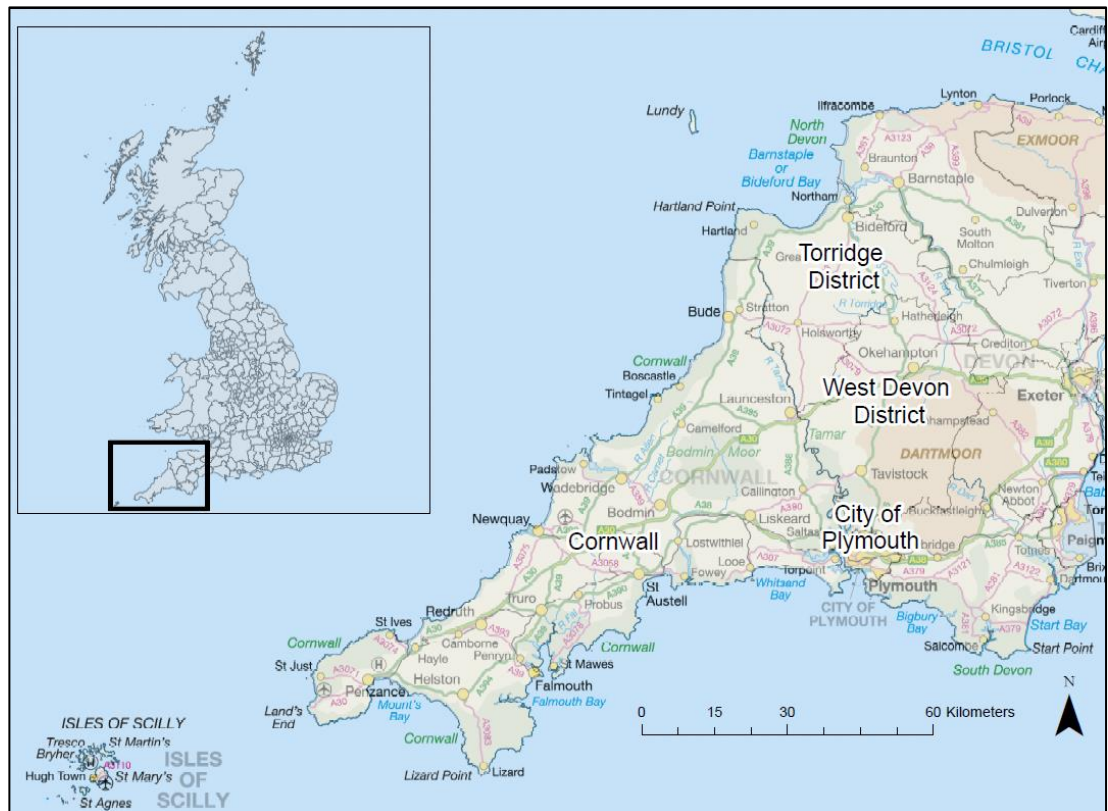
Figure 4.1 - Location map to show Cornwall and neighbouring districts

    OS Base map is © Crown copyright/database right 2011. An Ordnance Survey/EDINA supplied service.

Cornwall was ranked second from bottom in the UK in 2009 in terms of its Gross Value Added (GVA), an indicator of the value of the counties contribution to the UK economy (Community Intelligence, 2010, p1). The former Penwith and Kerrier local authority districts (now amalgamated as part of the Cornwall Unitary Authority) are some of the most deprived in the UK (South West Observatory, 2009) characterised by poor health, high unemployment, low income, and a long-term difficulty in attracting investment, compounded by poor accessibility "at the western end of a long narrow county" (Penwith District Council, 2004, Sec 2.3). The coast is an important resource and economic asset, supporting economic activities such as fishing and commercial port activities, alongside the leisure and tourism industry. Other traditional industries such as mineral extraction have suffered from decline and a lack of investment; particularly to the west of the county, and the dependence on low

skilled, low paid and seasonal occupations in the tourist industry have resulted in widespread deprivation. In the former Penwith District, over 20% of the population are employed in the tourism industry in some form (Deloitte, 2010), yet since jobs in this sector tend to be entry level, low paid and highly seasonal, gross disposable income per head is just £13,010 for Cornwall as a whole, compared to a GB average of £14,920 (Community Intelligence, 2010).

Tourism is recognised as one of Cornwall's most valuable industries and has supported improvements in infrastructure and service provision over the last few decades (Cornwall Single Issue Panel, 2004). The (now dated) Cornwall Structure Plan outlines the long-term development priorities for the county and recognises the importance of tourism as a much needed driver of development and regeneration, stating that "improvement in [tourist] facilities is also vital to the regeneration of the main coastal resorts" (Cornwall County Council, 2004, p38). As a result of tourist demand, coastal resorts such as Newquay, St Ives, Bude and Padstow enjoy facilities that exceed the usual expectations for centres of their size. This is especially true in terms of the provision of grocery stores, with resorts such as Newquay and Bude exhibiting grocery retail floor space and provision beyond that which would be reasonably expected for a residential population of their size (GVA Grimley, 2010).

Individual resorts and destinations are introduced separately throughout the subsequent Chapters if they form a key part of the discussion or modelling. Drawing on the discussion from Chapter 2, section 4.3 introduces the stores, both located in major resorts, that form the basis of the analysis carried out within this chapter.

4.3   Seasonal trading variations

4.3.1   Sainsbury's study stores

Section 4.2 introduced the tourist sector in Cornwall, where stores in popular tourist resorts experience considerable seasonal demand uplift driven by visitors. This chapter is predominantly concerned with stores in the popular resorts of Newquay and Bude, which both experience seasonal sales uplift during the summer months (see Figure 4.2). These stores both opened in July 2009 occupying former Somerfield stores and both are located centrally within the popular coastal resorts, close to beaches, transport links and other services and attractions used by visitors.

Table 4.1 highlights the basic characteristics of each store based on the company's own data and market share analysis (Sainsbury's, 2011a). Stores in Truro and Bodmin, which function less as tourist resorts, are also considered. These stores serve more of a residential population yet still play an important role in providing facilities for visitors. Truro represents a large-format superstore offering a greater choice and range than Sainsbury's other stores in this area, whilst the Bodmin store is highly accessible to residents and visitors via the A30 primary route (see Figure 4.2). It is thus important to understand the trading characteristics

of these stores, alongside Newquay and Bude, in order to model the interaction between demand and supply in subsequent Chapters.

Figure 4.2 - Sainsbury's Cornish store network

> OS Base map is © Crown copyright/database right 2011. An Ordnance Survey/EDINA supplied service. Used with permission.

Table 4.1 - Characteristics of selected Sainsbury's stores in Cornwall

	Bude	*Newquay*	*Bodmin*	*Truro*
Store size	11,507 Sq Ft	22,616 Sq Ft	22,401 Sq Ft	63,983 Sq Ft
Store type	Town Centre	Town Centre	Town Centre	Free Standing
Population within a 15 minute drive time	13,129	24,358	19,687	36,295
Market share within a 15 minute drive time	10.4%	12.7%	11.8%	24.0%

Sainsbury's guided the selection of stores which form the basis for this chapter. At the time (late 2010), the Newquay and Bude stores had traded for 18 months, with post-investment review by the location planning team identifying that revenue predictions had considerably underestimated seasonal sales uplift at these stores. During 2010, the team reported that sales at the Bude store were found to more than triple during the school summer holidays, which

the company believed to be attributable to additional demand driven by visitors staying nearby (Feltham and Davis, 2010).

The inclusion of such highly seasonal stores provides a useful opportunity to explore the characteristics and impacts of visitor demand at a store-level. Sainsbury's have supplied trading data for the four study stores for the year 2010. This includes total store transactions and revenue, broken down by trading week (Sunday – Saturday) (section 4.3.2), alongside net sales by product category on a weekly basis (section 4.3.3).

4.3.2 Seasonal sales uplift

Figure 4.3 illustrates Sainsbury's weekly sales figures (total revenue) for the four stores of interest during 2010. The sales data are displayed relative to a base level which represents the lowest recorded weekly sales for each store during the same period and allows easy comparison between stores, removing the impact of store size on total revenue, whilst also preserving confidentiality. Figure 4.3 demonstrates that there are clear seasonal sales fluctuations. All four stores experience sales uplift during the Christmas and Easter periods, traditionally periods of sales uplift driven by increased household spend. At the Bodmin and Truro stores, sales roughly double (compared to their lowest recorded sales) during the Christmas period.
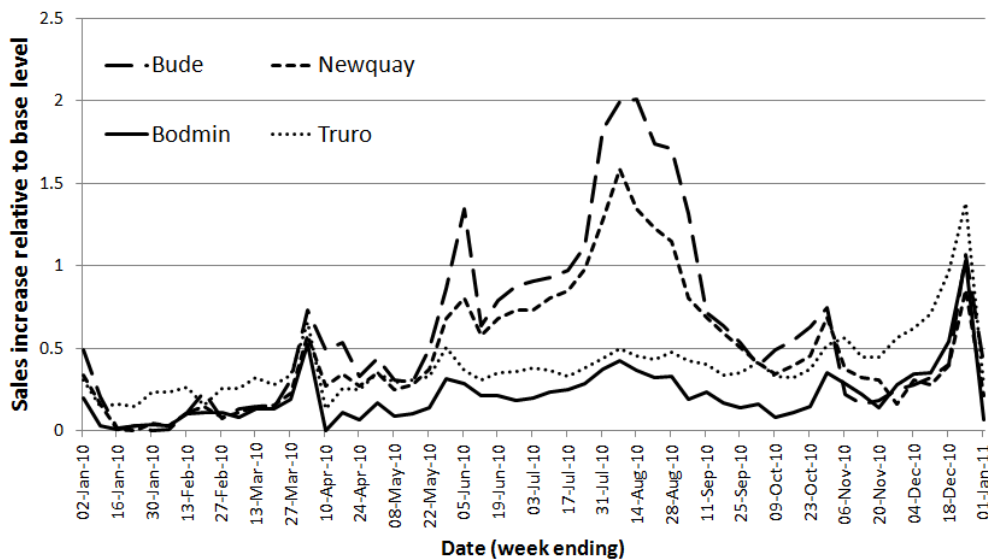
Figure 4.3 - Seasonal sales fluctuations at a store-level.

> Sales increase shown relative to a base level of zero, representing the lowest weekly sales at each store.

The coastal resort stores in Newquay and Bude demonstrate very pronounced sales peaks during the summer, undoubtedly driven by visitor spend. During summer 2010, the Bude store experienced average weekly sales which at one point represented a threefold increase compared to their average January values. Smaller sales increases around the school half term holiday in October/ May and the late May bank holiday are also evident and would be expected since these are all key periods during the tourist season.

The provision of self-catering accommodation in these resorts, coupled with increases in visitor numbers at these times of year (see Chapter 3), suggest that this form of uplift is likely to be attributable to overnight visitors. Similarly, the lowest sales were recorded during January/February and November, which represents the low-season in terms of tourism within Cornwall. Bodmin and Truro demonstrate less seasonal fluctuation around key holiday periods. This is not unexpected, since these stores tend to serve more of a residential and workplace customer base in areas with a lower provision of visitor accommodation.

Based on these sales values, the trading intensity (sales per square foot) (Table 4.2), is seen to fluctuate considerably during the year. Trading intensity is commonly used as an indicator of store performance, with Sainsbury's reporting that their UK estate trades at an average intensity of just over £20 per Sq Ft per week (J Sainsbury Plc, 2013). It is clear from Table 4.2 that these Cornish stores are trading well-below this intensity, particularly in the low-season, when trading intensity falls to less than £10 per Sq Ft per week in all but the Truro store. Nonetheless, in the peak summer season, trading intensity increases to its maximum value (at the Newquay and Bude stores), in line with company average, suggesting that peak season demand uplift contributes to the viability of these stores, which appear to trade well-below company average at certain times of year.

Table 4.2 - Trading intensity for Cornish study stores during 2010.

Sales per square foot based on recorded store revenue on a week-by-week basis.

Trading Intensity	Newquay	Bude	Bodmin	Truro
Average	£12.01	£11.72	£10.72	£15.03
Minimum	£7.43	£7.86	£8.83	£12.15
Maximum	£22.39	£20.34	£17.95	£25.60

In spite of the clear increase in sales at certain times of year, the average transaction value (as shown by Figure 4.4) tends to show little seasonal fluctuation, with the exception of a noticeable increase around Christmas and Easter. These fluctuations are likely to result from additional household expenditure on food and drink at these times of year and represent a demand uplift driven by the existing residential demand, rather than additional external demand inflow. Since average transaction values do not increase within Newquay and Bude in the summer months, sales uplift at this time of year must be driven by additional customer demand in the form of an increase in the number of customers and overall transactions,

rather than simply an increase in spending by existing consumers (which would be reflected in higher transaction values, as witnessed during the Christmas period).

The average transaction value at the Bude and Newquay stores is around half that of the larger Truro store, yet the pattern of fluctuation over the year is almost identical and, at an aggregate level, there is no recognisable impact of visitor demand on average transaction values. The Bodmin and Newquay stores are of a comparable size, thus the noticeably lower transaction value at the Newquay store (more in line with that of the smaller Bude store) may suggest that the Newquay store is trading below the levels that would be expected for a store of its size. This is addressed within the modelling reported in Chapter 7.

Sales figures presented from these Sainsbury's stores clearly demonstrate the seasonal component to store-level sales and revenue, particularly at the Newquay and Bude stores. Visitor numbers have also been shown to exhibit a high degree of seasonality in resorts such as these (see Chapter 3), with documented impacts on business and services in these towns (for example see Gordon and Goodall, 2000; GVA Grimley, 2010). However, aside from key periods such as Easter and the school summer holidays, during which it is well documented that visitor numbers increase, it is difficult to correlate store sales with key indicators of the tourist sector.
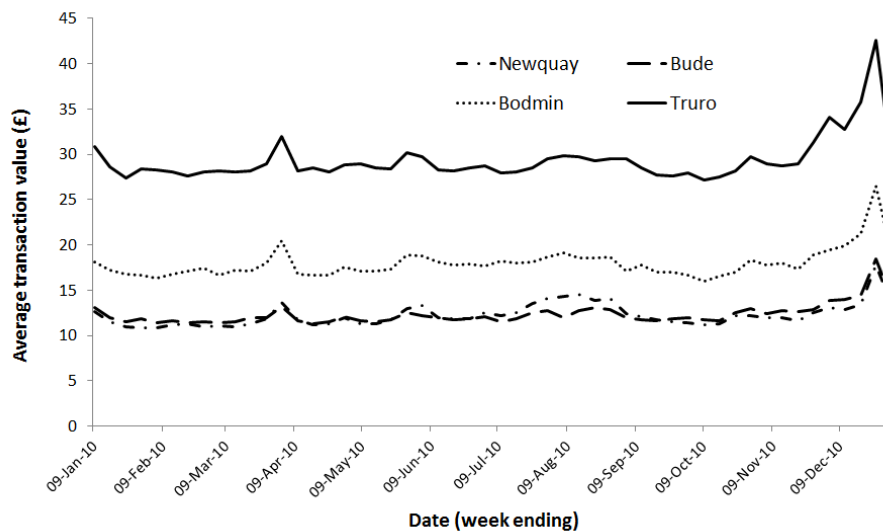
Figure 4.4 - Seasonal variation in average transaction values

At a destination level, overall visitor numbers (or their seasonal fluctuations) are difficult to obtain, and therefore cannot be directly compared to observed store-level seasonal sales uplift. Nonetheless, surveyed occupancy rates (South West Tourism, 2010c) for visitor accommodation serve as a useful proxy to indicate variations in the number of overnight visitors that may be present within these resorts. The Newquay store, for example, demonstrates a clear link between seasonal sales uplift and accommodation occupancy, particularly when self-catering accommodation is considered. Most notably, the period with the highest recorded sales also represents the month with the highest self-catering

accommodation occupancy (August), whilst the lowest sales coincide with the period in which lowest occupancy rates are recorded (January). This relationship was tested using linear regression with self-catering occupancy rates as the independent variable, thus suggesting that accommodation occupancy, as a proxy for visitor numbers, drives recorded store sales. The coefficient of determination (R^2) is 76.6% at the 95% confidence level for Newquay and 73.1% for Bude, suggesting that around three quarters of the total variation in store sales could be accounted for by the differences in self-catering occupancy rates.

At an aggregate level, there is thus clear indication that the seasonal sales variations experienced at these coastal resort stores are largely driven by visitor demand. The magnitude of demand uplift has been demonstrated to vary considerably on a week-by-week basis. This suggests that the use of simple up-scale factors to account for visitor demand within location-based modelling is potentially misleading, since no up-scale factor can account for the degree of variation evident on a week-by-week basis. In order to fully understand the nature and store-level impact of demand uplift (such that store revenue can be accurately estimated) it is important to consider the actual sales that make up that demand uplift. Section 4.3.3 begins by disaggregating overall store sales by product category, identifying the supply side impacts of seasonal demand uplift. Section 4.4 then focuses on the demand side, using loyalty card data to explore the characteristics and expenditure habits of external trade, including trade by consumers thought to represent visitors.

4.3.3 Seasonal sales fluctuations by product category

Sainsbury's made product-category level data available for a representative week in January (week ending 23rd January 2010) and August (week ending 7th August 2010), representing the low and peak seasons respectively. Data was provided for the Newquay and Truro stores, the two largest coastal and non-coastal stores included within the study. Section 4.3.2 has noted that the pattern of seasonal sales uplift is most pronounced between January and August, and that the Newquay and Truro stores exhibit very different seasonal sales characteristics, with the peak season demand uplift far more pronounced at the Newquay resort-based store.

The product categories considered within this section are shown in Table 4.3 and represent broad sales categories and easily identifiable in-store ranges such as 'health and beauty', 'dairy' and 'produce' (fruit and veg). Given that the Truro store is far larger than Newquay, comparison of the actual volume of sales between stores is meaningless. On a category-by-category basis, the difference in relative sales increase between January and August can be used to note the extent to which different product categories contribute to the observed sales uplift in each store between the low and peak tourist seasons. Table 4.3 identifies the percentage change in sales revenue on a category-by-category basis between the selected weeks in January and August. Based on the weekly sales data, overall store revenue at Newquay increased by 159%, and at Truro by 30% during the same period. Thus, product

Table 4.3 - Percentage change in sales by product category between low and peak season in 2010.

Product category	Newquay (159%)			Truro (30%)		
	% change Jan-Aug 2010	% of store rev. in Jan 2010	% of store rev. in Aug 2010	% change Jan-Aug 2010	% of store rev. in Jan 2010	% of store rev. in Aug 2010
Bacon and Sausages	212.9	1.6	2.1	31.5	1.7	1.8
Beers	505.2	3.5	8.5	114.1	1.7	2.8
Books	465.3	0.0	0.1	88.0	0.2	0.3
Carbonated Drinks	405.0	0.4	0.8	78.2	0.3	0.4
Cards and Wrap	65.7	0.4	0.3	14.5	0.5	0.4
Cereal	159.6	1.4	1.5	23.1	1.9	1.8
Confectionery	179.1	3.1	3.4	41.6	3.0	3.4
Crisps & Snacks	294.4	1.3	2.9	46.9	1.3	1.6
Dairy	127.4	8.4	7.7	26.6	8.4	8.5
Entertainment	131.8	1.8	1.7	24.1	1.8	1.8
Floral & Plants	54.9	0.4	0.3	1.2	1.0	0.8
Frozen Foods	89.5	3.3	2.5	30.0	2.6	2.7
Health & Beauty	164.3	3.3	3.5	21.7	4.8	4.7
Homeshop	-40.5	1.8	0.4	-50.2	2.2	0.9
In-Store Bakery	202.3	1.7	2.0	54.1	1.0	1.2
Laundry	-8.6	0.1	0.0	- 50.7	0.3	0.1
Major Electrical	-86.2	0.2	0.1	38.0	0.6	0.7
Meat, Fish & Poultry	113.3	5.8	5.0	11.3	5.2	4.6
News & Magazines	117.0	1.5	1.3	40.9	1.1	1.3
Packaged Grocery	93.9	7.3	5.7	12.4	8.1	7.3
Produce	132.6	8.9	8.3	31.2	11.0	11.6
Sandwiches	596.1	0.8	2.1	33.9	0.6	0.7
Spirits	355.5	2.3	4.3	36.8	1.9	2.0
Suncare	953.1	0.1	0.3	208.4	0.0	0.1
Toilet Paper	96.46	0.7	0.5	23.4	1.0	1.0
Water	487.9	0.3	0.6	56.1	0.3	0.4
Wines	153.5	5.4	5.4	66.7	4.8	6.4

categories with a revenue increase greater than 159% (at Newquay) or 30% (at Truro) experienced a relative seasonal sales increase that is greater than would be expected. Table 4.3 also shows the proportion of total store revenue accounted for by each category during January and August 2010.

Table 4.3 clearly shows that within Newquay, almost all product categories experience sales uplift during the tourist season, which would be expected, since overall store revenue more than doubles. Greatest revenue increases are experienced for sandwiches (for which sales increase by almost 600%), beers (over 500% increase), bottled water, books and carbonated drinks. This is unsurprising since within a coastal resort such as Newquay, these are likely to be popular items purchased for immediate consumption by visitors to the resort and its beaches. The relative increase on both sandwiches and beers is more than three times greater than overall revenue increases, suggesting that considerable demand uplift exists on these product categories.

With the exception of beers and sandwiches (which contribute 8.5% and 2.1% of Newquay store revenue in August) (Table 4.3) the product categories that experience the greatest sales increase contribute a minor proportion of overall store revenue – books, for example, represents only 0.1% of Newquay store revenue for the selected week in August 2010. Given that products such as sandwiches have a short shelf life, the considerable sales increases witnessed at the Newquay store during the peak season may generate a number of operational challenges in terms of forecasting demand for these products (Whitehead, 2010).

At Truro, the same product categories are also those with the biggest seasonal increase, although the magnitude of increase is far less, with only beers experiencing sales that more than double. Since Truro supports far more of a residential customer base, this disparity between the relative sales increase at Newquay and Truro on those categories suggests that it is indeed visitor demand that contributes to a significant sales uplift on product lines such as sandwiches, books, beers and other bottled drinks. Categories that actually saw a relative decrease in sales at both stores include cards and wrap, floral and plants, homeshop, laundry and major electrical. This may reflect the fact that visitors are less likely to purchase from these categories, or that less store space is devoted to these items during the peak tourist season.

At Newquay, core product categories that contribute a greater proportion of store revenue such as dairy, produce, packaged grocery and meat, fish and poultry actually experience sales increases that are below the store average for the same period, thus declining in relative importance during the peak tourist season. Within Truro, the corresponding core product categories show less variation in terms of their contribution to overall store revenue, suggesting that residential demand for these categories remains fairly stable between the low and peak tourist season, whereas visitor demand generates sales growth on other product

categories. Newquay benefits from a large and varied accommodation stock and as a result it was hypothesised that certain other product categories may experience sales uplift during the peak-season. In particular, 'bacon and sausages' and 'cereal' would be expected to increase, with an influx of visitors and even small accommodation operators purchasing these lines as breakfast items, whilst other household items such as toiletries, newspapers and magazines etc. may also be expected to increase as both visitors and accommodation providers are likely to purchase these. In reality, the observed sales increase on these categories are below or in line with the stores overall sales increase, and thus appear to demonstrate little impact from visitor sales.

In order to explore the link between seasonal visitor sales and specific product types further additional customer level data for both visitors and local residents would be required, detailing the actual products purchased. Unfortunately this does not form part of the dataset that was made available for this thesis. However, the store-level sales by product category suggests, in common with the overall store sales data, that observed sales fluctuations at stores such as Newquay are likely to be driven by fluctuations in visitor demand, since the products which experience considerable demand uplift are some of those that are highly likely to be purchased by visitors. However, given the minimal contribution that most of these product categories contribute to overall store sales, and the limited data available at this level, analysis of specific products is not considered further.

Nonetheless, the store-level data has clearly demonstrated that the Bude and Newquay stores exhibit a pronounced seasonal trade pattern, with seasonal fluctuations in store revenue thought to be largely attributable to an influx of visitors boosting overall sales and generating additional demand for some product categories. This chapter now makes use of customer level transaction data from the Nectar loyalty card scheme to explore the nature of consumer demand that is driving the seasonal sales fluctuations at these stores.

4.4   Using loyalty card data to identify external trade

4.4.1   Nectar card dataset

Chapter 2 noted that loyalty card data has become an important tool for grocery retailers. Well-established loyalty schemes generate data and customer insight which have proved fundamental in allowing grocery retailers to understand their customers and adapt their business to meet consumer needs. Chapter 2 highlighted some of the customer and store–level insights that can be gained from analysis of loyalty card data, which are themselves very rarely available for academic investigations. The provision of customer and transaction level data collected by Sainsbury's (via the Nectar card scheme) allows considerable insight into the nature of consumer expenditure in tourist resorts. These data allow consumer expenditure to be linked to unique customer identifiers, which in turn can be used to provide

an indication of customer spatial origin, geodemographic characteristics and usual consumption habits.

Sainsbury's were prepared to make 52 weeks' worth of loyalty card data available for this thesis. This could either be drawn from one store (in order to explore week-by-week sales fluctuations in one store over an entire year), or a total of 52 weeks' worth of data drawn from the four stores of interest within the study area. The loyalty card data obtained is shown in Table 4.4. Given the degree of seasonality evident at Newquay and Bude, obtaining data from these stores to represent a range of different time-points during the tourist season was important. At almost twice the size of the Bude store, Newquay attracts around twice as many transactions per week (in August). A considerable proportion of the loyalty card data was thus collected for Newquay given the highly seasonal element to trade and the volume of data available. All Nectar card data supplied was for the 2010 calendar year, in common with the store-level data.

A total of 24 weeks' worth of data were obtained for the Newquay store, representing all school holiday and bank holiday periods, plus a sample of weeks from the low season. This was supplemented by 12 weeks' worth of data for the Bude store, covering key school holiday periods, along with representative weeks from the low and fringe seasons. As the largest store in the area, 12 weeks' worth of data was also collected for the Truro store, representing the same weeks from the peak, fringe and low seasons for comparability with Bude. An additional 4 weeks' worth of data from Bodmin provide a comparison during the low, fringe and peak season for this less-seasonal store. The week is considered to be an appropriate unit of analysis within both the tourist sector and the grocery industry. All store-level data provided by Sainsbury's was organised by trading week. The week also forms a common unit of time for self-catering holidays, which are predominantly bookable on a weekly basis. Thus, visitor spend can be considered on a week-by-week basis for each store, allowing seasonal variations to be identified.

For the selected weeks and stores of interest, every in-store transaction linked to an active loyalty card has been recorded and made available in its raw format. These data were supplied as a series of excel spreadsheets, each representing one weeks' worth of transactions in one store. Within each file, every transaction linked to an active loyalty card is listed. Each record contains a unique customer ID numer (related to their loyalty card), the transaction value and the customer home postcode, the latter being based on information provided at registration into the Nectar scheme. An example is shown in Figure 4.5. There were over 4 million transactions recorded across the four study stores during 2010, of which just over 1 million took place during the study weeks. Almost 500,000 of these transactions were attributable to a customer loyalty card, representing just over 100,000 unique customers. These customers form the basis of the analysis reported below, with all non-loyalty card transactions excluded. It must be acknowledged that this dataset represents only a subset of all visitors to the selected destinations and care must be used when considering

the findings. In particular, this dataset only considers those customers holding and using a Nectar card. It is reasonable to assume that loyalty card usage may be lower among visitors as many may not hold a Nectar card (as they frequently shop with an alternative retailer) or may omit to bring or use their loyalty card whilst on holiday away from home.

Table 4.4 - Overview of loyalty card data used for analysis

Week ending	Newquay	Bude	Bodmin	Truro
Low Season				
23-Jan-2010	X	X	X	X
13-Feb-2010	X			
Spring Term School Half Term				
20-Feb-2010	X[1]	X		X
Easter				
03-Apr-2010	X	X	X	X
10-Apr-2010	X	X		X
Early Summer – including Whitsun bank holiday and school half term				
24-Apr-2010	X			
08-May-2010	X			
22-May-2010	X	X		X
29-May-2010	X	X		X
05-Jun-2010	X	X		X
Early Peak-Season				
19-Jun-2010	X	X		X
10-Jul-2010	X			
Peak Summer School Holiday				
07-Aug-2010	X			
14-Aug-2010	X	X	X	X
21-Aug-2010	X			
28-Aug-2010	X	X	X	X
04-Sep-2010	X			
Late Summer				
11-Sep-2010	X			
25-Sep-2010	X			
Autumn Term School Half Term				
30-Oct-2010	X	X		X
Low-Season				
20-Nov-2010	X	X		X
11-Dec-2010	X			
Christmas and New Year				
25-Dec-2010	X			
01-Jan-2011	X			

X Indicates that loyalty card data is held for corresponding week
[1] Loyalty card data were obtained for the Newquay store during this week, but inconsistencies in recording mean that they have been omitted from all subsequent analysis.

The Newquay and Bude stores experience lower Nectar card usage than many other Sainsbury's stores. In each of these stores, and for the corresponding trading year, the proportion of total in-store spend attributable to an active Nectar card was less than 60% (based on Sainsbury's own analysis) compared to rates commonly above 80% across their store portfolio. This is likely to be a combination of the fact that these stores represent relatively new investments within Sainsbury's network and also a result of the large numbers of visitors using these stores. As stores that were still establishing themselves within the local retail hierarchy at the time these data were collected, loyalty card use may be yet to reach its potential. Nonetheless, this data set affords a unique opportunity to identify transactions linked to consumers that are thought to originate from outside the stores' usual catchment area, as outlined in section 4.4.2.

Figure 4.5 - Example of Nectar loyalty card data in its raw format.

> Extract shown is for the Bude store (week ending 28th August 2010). Inset shows additional sales (in other Sainsbury's stores) for one selected customer, discussed in section 4.6.

4.4.2 Disaggregation of loyalty card trade by spatial origin

Card holders home postcodes have been obtained for each transaction attributable to a loyalty card. Consequently, each transaction can be categorised according to the spatial origin of that customer, based on their self-reported home postcode. On a store-by-store basis, home postcode has been assigned spatial reference information allowing loyalty card trade to be subdivided by spatial origin into the following groups:

a) **'Local residents'** are those customers using a loyalty card registered to a home postcode falling within the trade area of the store in which the transaction took place. The trade areas have been defined by Sainsbury's and are based on their in-house market share analysis using loyalty card data at the Census Output Area (OA) level.

An OA is the lowest level of aggregation for the dissemination of census and administrative data in the UK, representing an average of 124 households (Vickers and Rees, 2006).

b) **'External trade'** includes all customers using a loyalty card registered to a home postcode falling outside the trade area for the store in which the transaction took place. They have been further divided into:

   i. **'Overnight visitors'** are those customers using a loyalty card registered to a home postcode that is over 61 miles from the store in which the transaction took place. A distance of 61 miles was chosen as the threshold to identify visitors staying overnight since the England Leisure Visits Survey (ELVS)[7] identified that for coastal resorts, day trip visitors had travelled an average of 61 miles from home (Natural England, 2005, p21). All visitors originating from a distance greater than 61 miles from the store are therefore more likely to be staying overnight within the area, and thus likely to exhibit higher expenditure on food and drink.

   ii. **'Local non-residential trade'** are therefore those customers using a loyalty card registered to a home postcode falling outside the trade area, but within a distance of 61 miles from the store in which the transaction took place and thus not considered to be overnight visitors. This group of consumers is likely to include tourist day visitors, but also a number of non-leisure visitors such as people living outside the store catchment but visiting the store during non-leisure trips related to other forms of personal mobility, such as work or education. Analysis has demonstrated that this group exhibits characteristics and expenditures that are similar to local residents. It has not been possible to extract leisure day visitors from this diverse group of customers. These consumers are included wherever 'external trade' is considered, but as it has not been possible to distinguish the exact make up of this group, these customers are not analysed further as a distinct sub-group on their own.

The flowchart and schematic diagram in Figure 4.6 further illustrates the sample of customers and transactions used within this analysis. Disaggregation of loyalty card trade by spatial origin suggests that external trade is an important component of sales at all four study stores (Table 4.5). Unsurprisingly, over 30% of loyalty card spend at the Newquay store, and almost 50% of loyalty card spend at the Bude store, is attributable to external trade (based on the spatial origin of consumer loyalty cards). Around a quarter of loyalty card spend at Newquay, and just under one third of loyalty card spend at Bude, is thought to be attributable specifically to visitors staying overnight. There are the primary interest of subsequent

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[7] At the time of analysis the ELVS represented the most up-to-date survey of day visitors. It has since been superseded by the GBDVS which is used for subsequent analysis in Chapters 5 – 8.

analysis as the literature has suggested that these consumers will contribute considerably to the observed seasonal sales uplift.
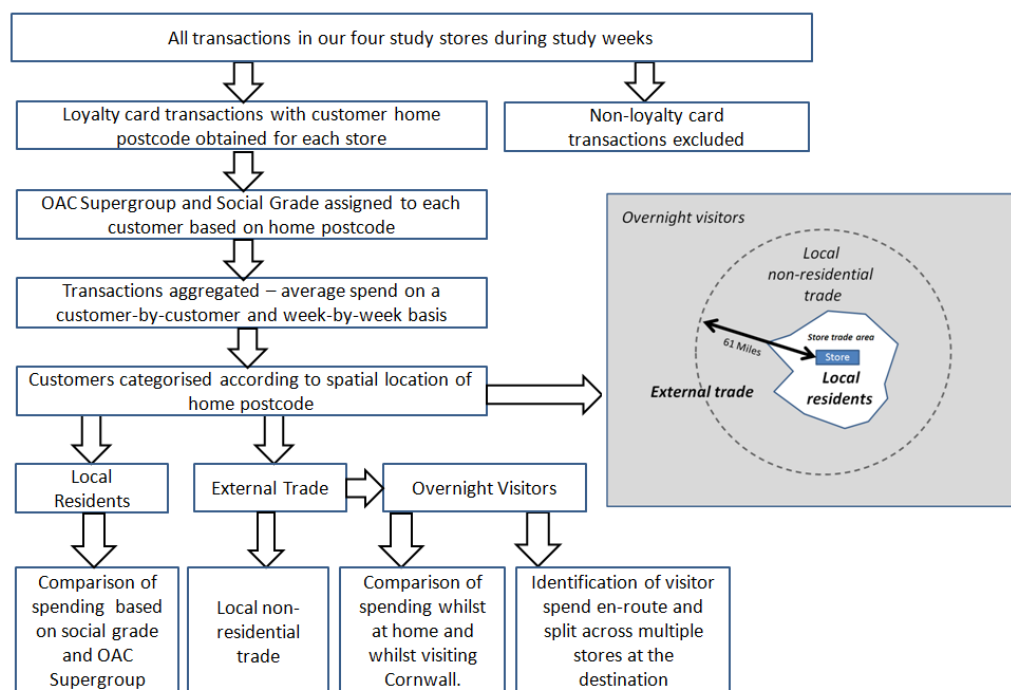
Figure 4.6 - Flowchart and schematic to illustrate the dataset used for the loyalty card analysis.

Visualising the spatial origin of trade (which is shown on Figure 4.7 for the Newquay store) reveals more about external trade at this store. Figure 4.7 accounts for the underlying population distribution (using 2010 mid-year population estimates) and considers the total number of loyalty card transactions per 100,000 people at the district level. Within the Newquay store, transactions that are attributable to external trade tend to show some degree of spatial clustering in terms of consumer origin. External trade (based on consumer home postcode) appear to originate from a number of major urban areas with an element of distance decay exhibited.

Table 4.5 - Loyalty card trade by origin for selected Cornish stores

Store	*Newquay*	*Bude*	*Bodmin*	*Truro*
Proportion of total loyalty card transactions attributable to external trade	29.4%	39.4%	27.5%	16.2%
Proportion of total loyalty card spend attributable to external trade	31.4%	47.3%	26.4%	16.6%
Proportion of total loyalty card spend attributable to overnight visitors	25.5%	32.1%	13.2%	8.9%

Figure 4.7 reveals that there are a number of districts which record a high number of transactions in the Newquay store, even though they are not geographically proximate to the store. Heavily populated areas closest to the south west tend to account for a greater number of recorded transactions in the store. In particular, there is a band stretching north east from Cornwall, through Devon, Bath and Bristol and into the West Midlands from which a high number of transactions are seen to originate. This is in common with the latest (2004) survey of visitors to the resort of Newquay, which found that 9% of all surveyed visitors originated from the West Midlands, and 5% from Devon and Somerset (South West Tourism, 2005b). These are some of the areas from which Newquay (and Cornwall in general) is most accesible, especially via the M5 motorway, and once again suggests that external trade recorded in store (and contributing to seasonal sales uplift) is driven largely by expenditure associated with overnight visitors.
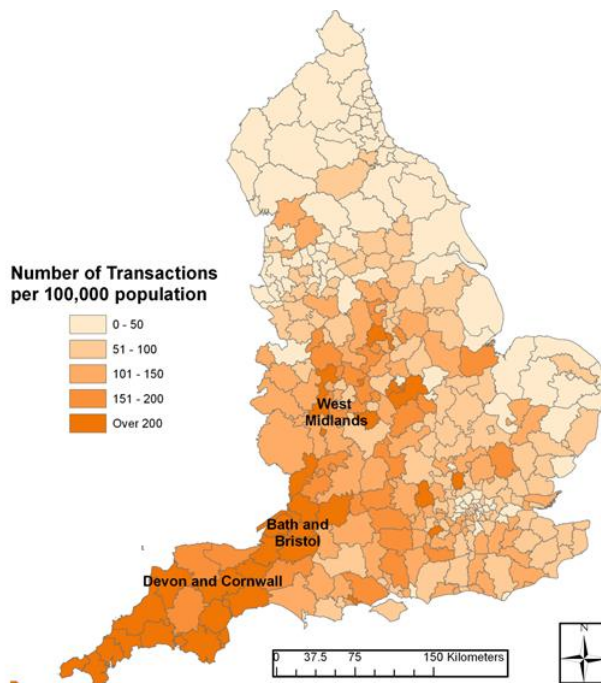
Figure 4.7 - Newquay store loyalty card trade by Local Authority District

 Number of transactions (per 100,000 people), based on 24 representative weeks during 2010.

In spite of not being recognised as a major tourist destination, table 4.5 suggests that the Bodmin store attracts over 25% of its revenue from external trade, likely to be a result of the store lying close to the main A30 transport route, heavily used by tourists and other visitors travelling through the county. Similarly, the city of Truro provides little visitor accommodation or principal attractions, yet attracts 16.6% of its total revenue (amounting to over £150,000 per week) from external trade (based only on the representative weeks for which data is held), of which around half is thought to be attributable to overnight visitors (no doubt in-part driven by proximity to the A39 road link). These observations suggest that

visitor sales forms an important component of trade at all four study stores. This is particularly true of stores in Newquay and Bude where high numbers of visitors, combined with relatively small stores, generates very noticeable sales uplift. The popularity of the Bodmin and Truro stores for external trade also suggests that stores located some distance from major resorts themselves may still benefit from seasonal visitor expenditure.

4.4.3   External trade by spatial origin and week

Since loyalty card transactions are reported by week (Sunday – Saturday), it is possible to identify seasonal variations in the proportion and spatial origin of external trade by week. Figure 4.8 identifies the proportion of loyalty card sales that make up external trade on a week-by-week basis at the Newquay store (note that only the weeks identified in Table 4.4 are included on Figure 4.8). Figure 4.8 reveals that during the peak tourist season, up to 50% of loyalty card trade and expenditure can originate from outside the store trade area at the Newquay store, falling to less than 15% during January and November. Figure 4.8 also identifies the proportion of external trade thought to be attributable to overnight visitors, which appears to peak, as expected, during the school summer holidays in August. In August, around 90% of external trade is thought to originate from overnight visitors, falling to around 50% of external trade during January, which coincides with the period of lowest overnight visitor numbers as inferred from occupancy rates. This suggests that day visitors travelling from home make up a greater proportion of external trade during the low season.
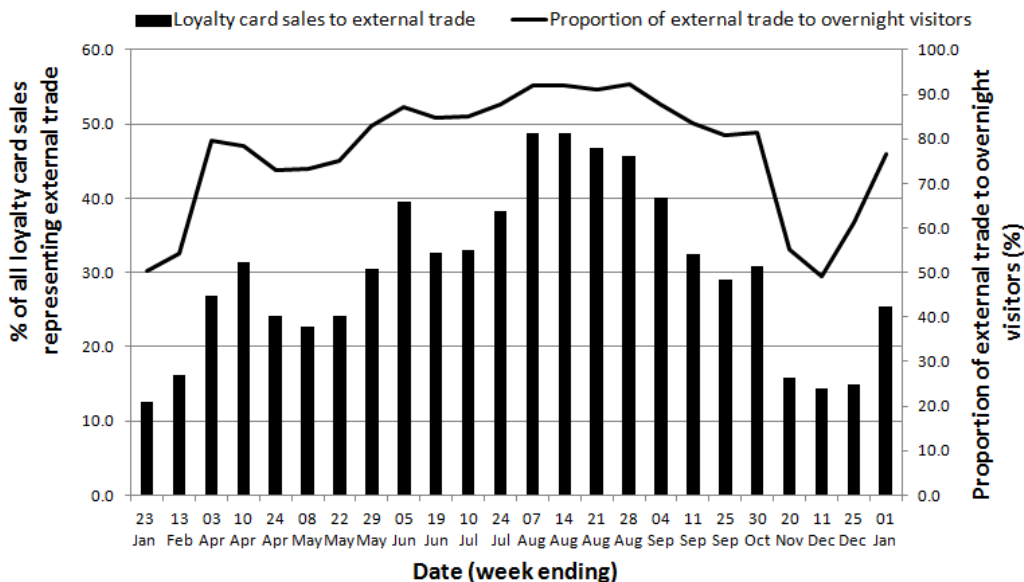
Figure 4.8 - Loyalty card sales by week for the Newquay store

Table 4.6 provides comparison with the Bude, Bodmin and Truro stores for up to 6 key weeks during 2010. Bodmin and Truro demonstrate noticeably less seasonal variation, with external trade doubling between the low and high-season at these stores. By contrast, external trade roughly quadruples at Newquay and Bude in the summer, and as much as triples at Easter and during key bank holidays and school holidays. Therefore, and as also

suggested by the aggregate level sales data, stores in the main coastal resorts appear to exhibit a clear seasonal component to their sales, attributable to external trade. These seasonal fluctuations are in line with expectations based on the survey data and seasonal tourism trends outlined in Chapter 3, with external trade increasing during the periods when visitor numbers and usage of overnight accommodation is known to be greatest.

Figure 4.9 identifies the spatial origin of trade by week, considering three weeks, taken from the low (January), fringe (October) and peak (August) season. In common with Figure 4.7 transactions recorded in the Newquay store are displayed based on consumers' home district. It is apparent that the pattern of consumer origin for transactions recorded in the Newquay store varies considerably by season. During the peak school holiday period in August, customers are seen to originate from districts across most of the UK, including notable clusters in the West Midlands and Yorkshire. During the October half term holiday, it can be observed that the overall number of transactions is lower and that customers are more likely to originate from areas that are more accessible. For example, clusters around Avon and the West Midlands, both linked to the M5 motorway, are apparent, with fewer customers originating from East Anglia, Kent and Sussex or the North East. The spatial disparity is most noticeable when comparing August with the low-season in January, during which almost all transactions originate within Cornwall itself, with very few districts recording any noticeable cluster of transactions outside Cornwall.

Once again, these spatial patterns are not unexpected given the lower propensity for overnight visitors to be present in the resort in January, resulting in trade being drawn primarily from within the store trade area or from residents of local districts passing through for work or leisure day trips rather than overnight visits. By contrast, the spatial pattern in August identifies that visitors travel considerable distances from across all regions of the UK. This again supports the assertion that the high degree of seasonal uplift experienced during the tourist season is driven largely by overnight visitors. Although not the focus of this thesis, the spatial patterns evident on Figure 4.9 should be considered by retailers in order to account for spending that will be displaced from consumers' 'home' stores, which may notice a seasonal sales reduction if large numbers of local residents are away from home.

These observations based on the loyalty card data are in common with the store trading data presented in section 4.3. They confirm initial assumptions that the seasonal trade uplift observed is largely attributable to spending by overnight visitors. This section now turns attention to considering the specific expenditures associated with loyalty card trade by origin in order to identify broad consumption habits associated with visitors.

Table 4.6 - External trade by week

Time of Year	External trade as a percentage of all loyalty card sales				Proportion of external trade to overnight visitors (%)			
	Newquay	**Bude**	**Bodmin**	**Truro**	**Newquay**	**Bude**	**Bodmin**	**Truro**
Low-Season	12.6	14.2	14.6	9.8	50.2	40.0	32.6	45.3
Easter	31.4	43.8	24.6	16.8	78.3	81.9	45.2	54.0
Whitsun	39.5	55.2	-	17.6	87.1	85.7	-	60.2
Summer	48.8	60.4	28.8	18.4	92.0	90.6	61.5	62.6
October Half Term	30.9	42.8	-	15.5	81.4	80.5	-	49.8
Christmas	14.9	24.6	-	-	61.4	70.3	-	-
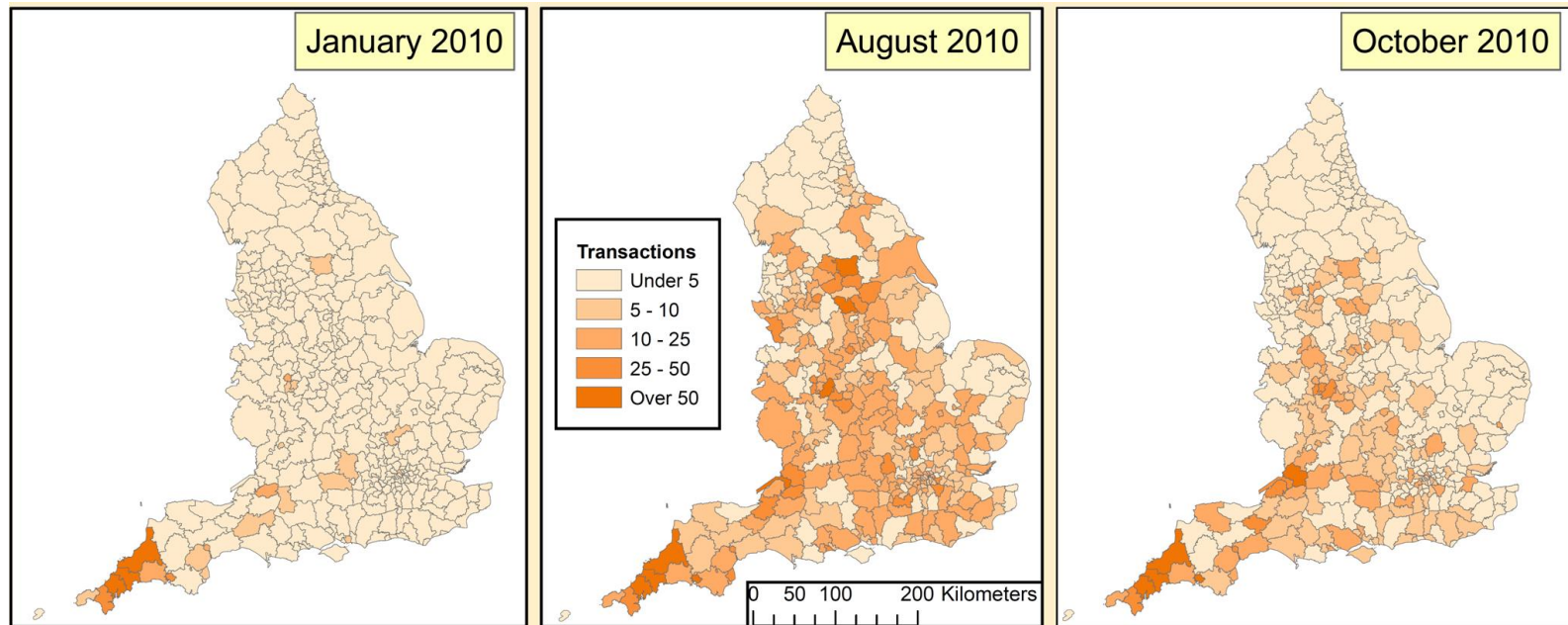
Figure 4.9 - Loyalty card transactions by district for selected weeks – Newquay store.

4.4.4   Consumer expenditure by spatial origin of trade

This section seeks to examine and compare the spending characteristics of local residents and external trade in order to understand more about the individual-level consumption associated with visitors and other external trade. This has been achieved by aggregating loyalty card transactions on a customer-by-customer, store-by-store and week-by-week basis such that total spend in any given store and week can be identified for each unique loyalty card holder, taking account of their spatial origin. The spatial origin of trade appears to have a clear impact on consumer's average weekly expenditure, as shown in Table 4.7

Table 4.7 illustrates that all forms of external trade at the Newquay store appear to spend less, on average, than local residents. A similar pattern is noted at the nearby Truro store. By contrast, at the Bude and Bodmin stores, visitors tend to spend more in-store than local residents. Even though Bude and Newquay are both coastal resorts, Table 4.7 suggests that visitors use these stores in slightly different ways. Within Bude, it appears that overnight visitors are likely to use the store for larger shopping trips than locals, perhaps due to its town centre location close to other attractions, whilst locals may be more likely to travel outside the town to shop elsewhere. Similarly, the Bodmin store appears to be a popular choice for visitors to stock-up on food and drink, perhaps en-route to destinations further west within the county, and implies that visitors tend to purchase larger basket sizes than local residents in this store.

Table 4.7 - Average weekly spend by spatial origin of trade

Average weekly spend	*Newquay*	*Bude*	*Bodmin*	*Truro*
Local Residents	£32.74	£27.27	£31.28	£54.31
External Trade	£27.59	£30.27	£35.50	£48.65
Overnight visitors	£28.33	£32.23	£38.26	£52.19

Consideration of average spend on a week-by-week basis (once again for the Newquay store) identifies that the average weekly spend by visitors varies at different times of year (Figure 4.10). Visitor expenditure is seen to fluctuate between an average of £25.00 and £34.00 per week (excluding Christmas), peaking during the school summer holidays in August. Visitor spend is thus higher during the summer months, when there is a greater propensity to use forms of self-catering accommodation such as camping and caravanning. Increased expenditure in the summer months is also likely to be driven by the increased party size at this time of year and suggests that these variations must be taken into account when attempting to model visitor expenditure (Chapter 5).

Variations in visitor spend, both between and within stores, suggest that differences within the stores themselves (e.g. size, range of products), their locations (coastal resort, major city, transport link) and the type of visitors that they may attract influence the proportion of external trade and the value of individual customer spend. Such differences cast considerable doubt on the suitablilty of revenue estimation based on any form of simple expenditure up-scaling, which cannot account for these seasonal and spatial differences, as discussed further in section 4.7. Customer loyalty card data are used in section 4.5 in order to understand more about the nature of visitor demand and to identify the consumption habits associated with individual groups of consumers, disaggregating trade by a geodemographic classification and by social class. The latter is considered first and provides an opportunity for comparison with surveyed information about visitors to Cornwall.
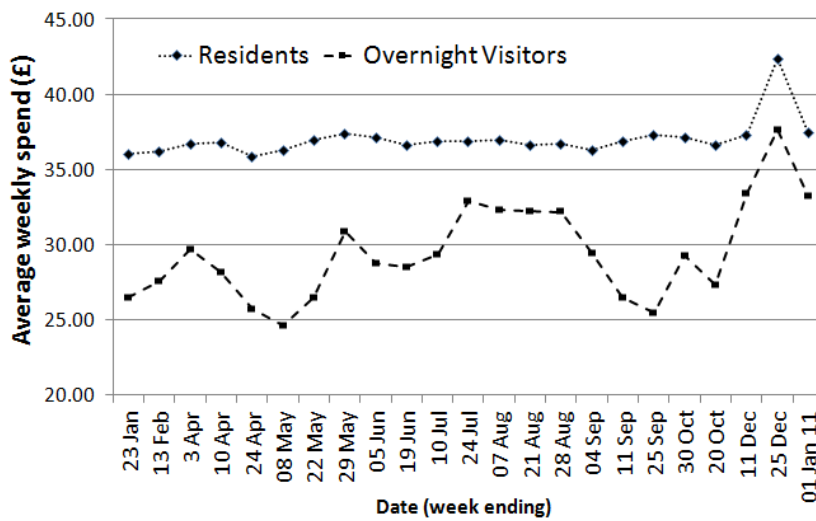
Figure 4.10 - Average weekly spend by week and spatial origin, Newquay store

4.5 Segmentation of loyalty card trade by geodemographic status

4.5.1 Social class

The social grade classification originating from the National Readership Survey (NRS) (NRS, 2012a) has become an established classification scheme for social class and is commonly used within surveys of tourism (Williams, 2008). The classification categorises households into one of six commonly recognised 'grades' ranging from 'higher professional' (A) through to 'On state benefit or unemployed' (E) (see Table 4.8), based primarily on the occupation of the chief household income owner. The Market Research Society (MRS) (2004) note that the classification is based on a range of household characteristics and can only be accurately determined by trained market research interviewers (Meier and Moy, 2004). However, the 2001 census results contain household level 'approximate social grade' (at the OA level), derived solely from the demographic and socio-economic variables in the census, which is considered to be at an acceptable level of accuracy to represent the true social grade for each household (Meier and Moy, 2004). Social grade has been assigned to

each customer based on their loyalty card home postcode, using the 'approximated social grade' from the 2001 Census Area Statistics[8].

Table 4.8 - Social grade classification

Source: Census Area Statistics Table UV050

Social Grade(s)	Description
AB	Higher and intermediate managerial/administrative/professional
C1	Supervisory, Clerical, Junior managerial/administrative/professional
C2	Skilled manual workers
DE	Semi-skilled and unskilled manual workers, On state benefit or unemployed

The use of social grade enables comparison between the social profiles of visitors that shop in the four Sainsbury's study stores compared with the profile of visitors to these destinations as reported by the UKTS. As introduced in Chapter 3, the UKTS is a sample survey of around 100,000 respondents per year in which participants are asked to recall characteristics of up to 3 recent domestic overnight trips (TNS, 2010b; VisitEngland, 2010). Figure 4.11(i) shows the social grade of visitors (proportion of visitor nights by social grade of respondent) to the South West (including Cornwall, Devon, Somerset & Avon, Dorset and Wiltshire) in 2010.

The UKTS highlights that visitors to this region as a whole fall predominantly (67%) within the more affluent ABC1 groups, whereas nationally only 55% of households fall within ABC1 groups (NRS, 2012b). By contrast, 2001 census data suggests that 35% of residents within these store catchments originate from less affluent social grades D and E (Figure 4.11(ii)). This corresponds very closely to the profile of local residents recorded in-store using Nectar card data (Figure 4.11(iv)), which suggests that the sample of Nectar card data used is able to accurately represent the profile of customers recorded in-store.

Figure 4.11(iii) shows the profile of overnight visitors recorded within the loyalty card data at all four study stores. This demonstrates little coherence with the UKTS social profile of visitors to the south west (Figure 4.11(i)), with a considerable under-representation of visitors from ABC1 social groups in the store trade compared to the profile of visitors. Furthermore, there are slight variations between the profile of visitors (Figure 4.11(iii)) and local residents (Figure 4.11(iv)) recorded in the loyalty card data for the four stores of interest. Section 4.5.2 seeks to unpick these characteristics further, making use of the Output

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[8] Table UV050

Area Classification in order to understand more about the profile of visitors recorded in these stores.
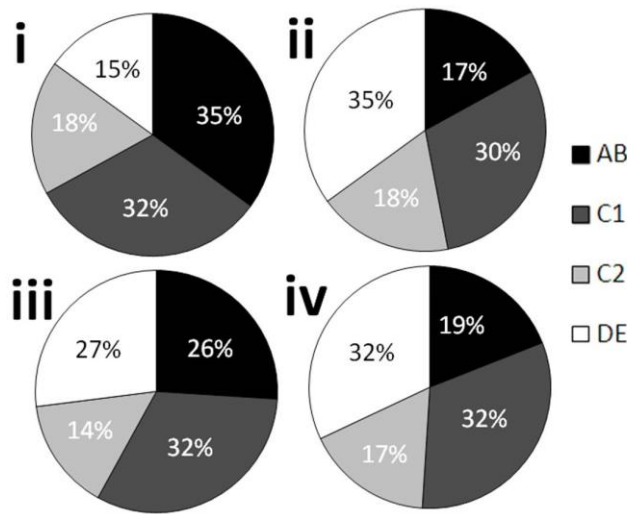
Figure 4.11 - Loyalty card trade by social grade

> (i) UKTS proportion of visitor nights by social grade (South West England) (2010), (ii) Local residents (Cornwall) by social grade (2001 census), (iii) overnight visitors by social grade (all four study stores) from Nectar card dataset (2010), and (iv) local residents by social grade (all four study stores) from Nectar card dataset (2010).

4.5.2 Output Area Classification

In order to fully explore variations in the characteristics of visitors and local residents, the Output Area Classification (OAC), part of the National Statistics Area Classification, has been used. The classification is based on 2001 census data and classifies all 175,434 OAs in England and Wales into one of 21 groups based on 41 census variables (Vickers and Rees, 2006). The variables used for the classification reflect the socio-economic nature of the households that make up each OA and include demographic, housing and employment characteristics. Thompson et al. (2012) also note that the OAC classification is the only geodemographic classification accredited as a National Statistic and thus represents an invaluable tool for identifying key small-area characteristics from the 2001 census. The 'Living Costs and Food Survey' (LCF) (ONS, 2010) is also reported by OAC group, which forms an important link to surveyed household expenditure data used within Chapter 5.

The OAC categorises households into one of seven 'supergroups', which are further sub-divided into a total of 21 groups. All customers using a loyalty card in one of the four Sainsbury's study stores have been assigned to the OAC supergroup for their home neighbourhood, allowing comparison of residential and visitor consumption by geodemographic status. OAC groups can be further disaggregated into 52 subgroups. However, due to the resultant small sample sizes (in some subgroups <50 customers), the OAC group level is the lowest level of disaggregation possible with this dataset.

As shown in Figure 4.12, the geodemographic nature of the trade varies markedly between local residents and external consumers. At all four study stores, local resident trade is dominated by households within the 'Countryside' supergroup and in particular group 3c 'accessible countryside' (for clarity, Figure 4.12 is at the supergroup level only). The dominance of supergroup 3 is unsurprising given the rural or semi-rural nature of the store catchments. At Newquay, around 40% of the residential trade is from supergroup 3, and over 50% at Bude, Bodmin and Truro. Supergroup 6 ('Typical Traits') also accounts for a third of local resident trade at Newquay, and around 20% at Bude, Bodmin and Truro (most notably for groups 6b 'least divergent' and 6c 'young families in terraced houses'). Again this is not surprising given the nature of the store catchments, with many areas of Cornwall representing non-affluent former mining communities.

Table 4.9 highlights the characteristics of the OAC supergroups that are most prominent within the loyalty card trade at these stores. Local resident trade is dominated by supergroups 3 and 6, which, in spatial terms, cover a large proportion of the UK's households, representing much of the rural population and a proportion of the slightly less-affluent urban population. According to the LCF (ONS, 2010), households in these supergroups spend between an average of £51.50 and £56.80 per week on food and non-alcoholic drink. These groups also spend up to a further £54.70 on alcohol, tobacco, and 'household goods and services', a proportion of which are likely to be purchased from grocery stores.

By contrast, overnight visitors are dominated by customers from the more affluent 'prospering suburbs' supergroup, accounting for around 30% of overnight visitor trade at all four stores. Visitor spend is, however, more evenly distributed across the seven OAC supergroups than residential spend. The dominant overnight visitor tends to be slightly more affluent than residential trade, displaying a higher average weekly food spend according to the LCF. In particular, groups 4b (prospering older families) and 4c (prospering semis) make up a significant proportion of overnight visitors and are under-represented within the local trade.

The pattern becomes more complex when recorded loyalty card spend by overnight visitors is considered in relation to spend by residents from the same OAC supergroup, as outlined in Figure 4.13. Here, visitor spend is shown as a proportion of residential spend in the corresponding store by residents from the same OAC supergroup. A value of 100 identifies that visitor and residential spend are identical, with values over 100 demonstrating that visitors from the given OAC supergroup spend more (on an average weekly basis) than local residents from the same OAC supergroup. It is immediately apparent that across all OAC supergroups, visitors spend more than residents in the Bude and Bodmin stores, even when they have similar geodemographic characteristics. This is particularly true for visitors from the 'city living' supergroup who are found to exhibit an average weekly spend of more than twice that of similar local residents in the Bodmin store (although a small sample size for visitors in this supergroup should be noted).
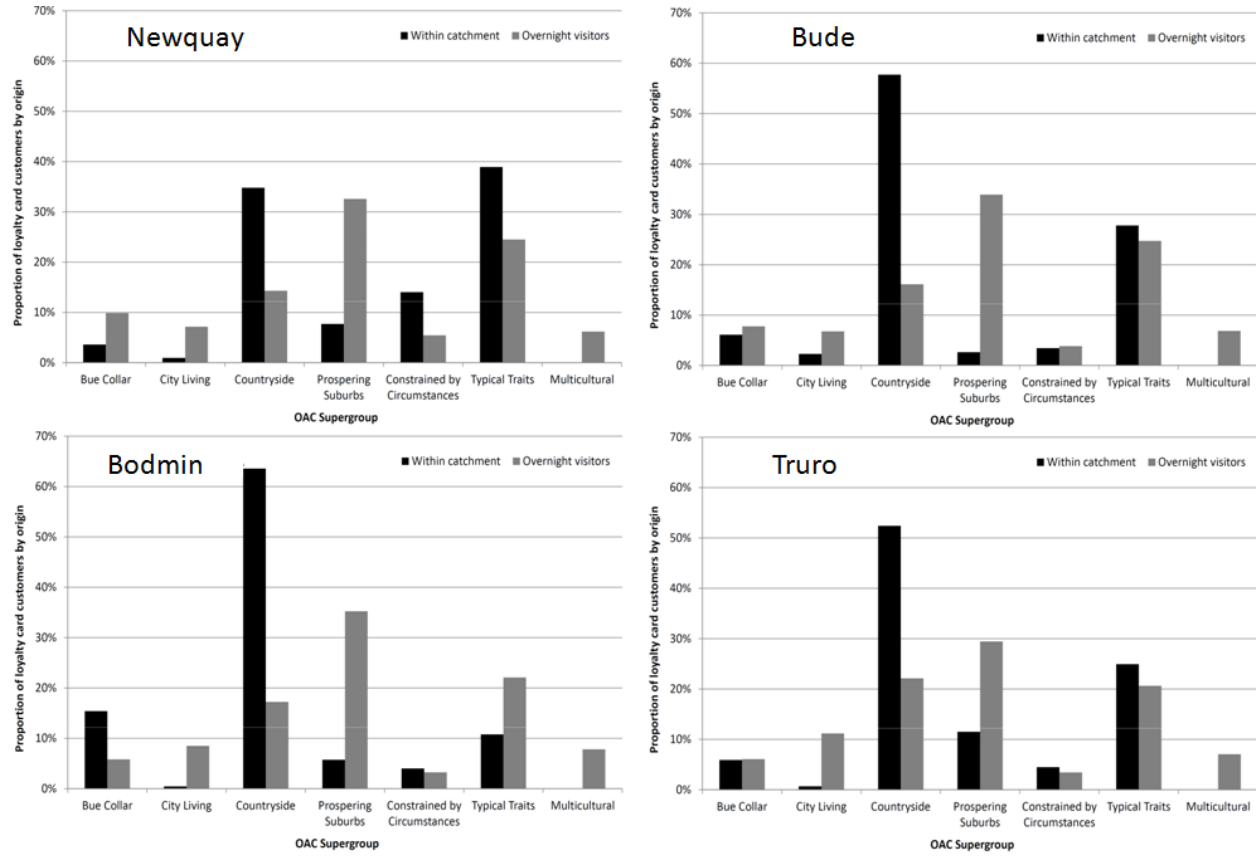
Figure 4.12 - Summary of loyalty card trade by origin, disaggregated by OAC group

	Local residents		Overnight Visitors
Predominant group	Group 3 - 'Countryside'	Group 6 - 'Typical Traits'	Group 4 - 'Prospering Suburbs'
Typical characteristics	Detached housing, 2 cars, age 25-64, no (dependent) children, working from home, work within agriculture/fishing.	Terraced housing, age 25-44, dependent children, private rental, working in manufacturing.	Detached housing, 2 cars, age 45-64, no (dependent) children, HE qualifications, work in Finance.
Typical locations	Widely spread across the UK being represented in all areas with the exception of major urban areas.	Spread across the UK, with notable clusters in all cities and major urban areas, notably Manchester and Leeds.	Spread across the UK, with clusters within commuting distance of major cities including London, Birmingham, Manchester, Leeds Newcastle and Cardiff.
Gross weekly household income	£775.90	£703.00	£844.80
Average overall weekly expenditure	£433.70	£380.00	£454.10
Average weekly expenditure – food and non-alcoholic drink	£56.80	£51.50	£60.10

Table 4.9 - Summary of OAC supergroup characteristics.

Sources (ONS (2010); Vickers and Rees (2006); Williams and Botterill (2006))
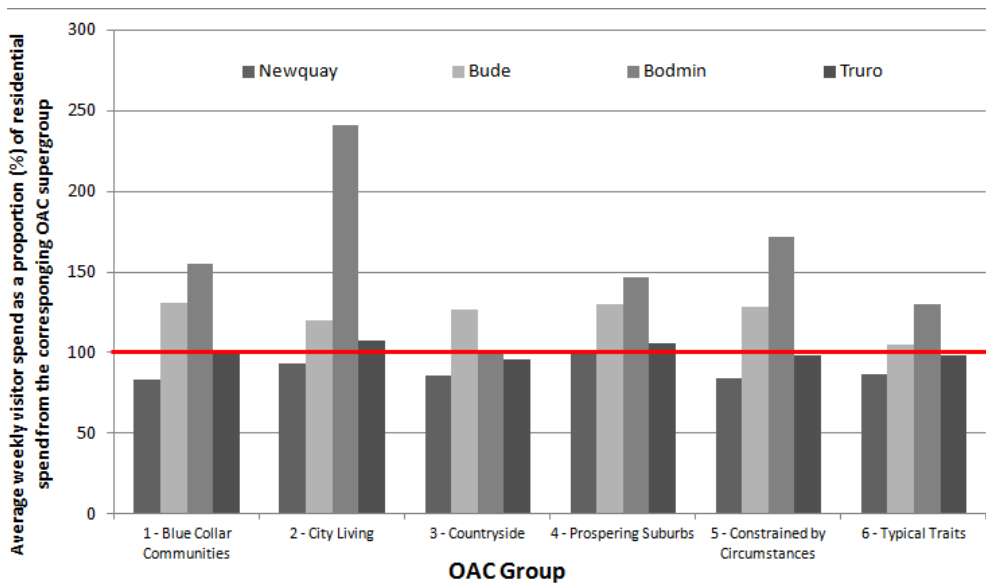
Figure 4.13 - Comparison of visitor and local resident spend by OAC Group

In common with the aggregate level data, Figure 4.13 suggests that overnight visitors from all OAC supergroups spend less than local residents in the Newquay store. However, the difference is least for those residents from supergroup 4 ('prospering suburbs'), from which over 30% of overnight visitors have been identified to originate. These findings suggest that some of the variation in average visitor spend between local residents and visitors may result from differences in their geodemographic characteristics which, in turn, may lead to different expenditure habits.

Therefore, any revenue estimation that attempts to account for visitor spend by simply up-scaling residential spend is unlikely to be able to account for these differences. As such, revenue estimation in these areas should be based, where possible, on expenditure estimates obtained for visitors and not simply up-scaled from residential demand (as discussed in section 4.7). First, however, section 4.6 makes full use of the loyalty card data by identifying broader consumption habits associated with overnight visitors, including their regular spend at home and any additional food and drink consumption linked to a Nectar card whilst in the destination.

4.6 Incorporating visitors' broader consumption habits

The loyalty card data allows visitor consumption recorded within the four study stores to be considered in the context of these consumers' broader grocery consumption habits with Sainsbury's. This section makes use of additional customer level data available from the Nectar scheme in order to consider how visitor spend within the four stores varies from these visitors' usual home consumption habits in similar stores. This section also attempts to consider the spatial pattern of loyalty card usage in the week immediately before and during a visit to Cornwall in an attempt to understand more about the complex spatial patterns of visitor spend.

4.6.1 Regular 'home' consumption

Since all visitors using a loyalty card within Sainsbury's study stores are identified by a unique ID number, all other transactions by these customers can be identified (see Figure 4.5). Comparisons can be made between consumers' regular home consumption and their consumption whilst visiting Cornwall. The term 'home consumption' refers to all other consumption by overnight visitors that shopped in one of the four Cornish study stores. Almost 15,000 customers are used for this comparison, yet it must be acknowledged that this dataset represents only a subset of all visitors to the stores and destinations, and care must be used when considering the findings. This dataset only considers those customers holding and using a Nectar card, so customers who frequently shop with Sainsbury's, but who omit to use their loyalty card whilst away, will not be included within the comparison. Consequently, the dataset may not reveal the full extent of consumers' shopping habits, but does provide a unique insight into differences in expenditure when consumers are away from home.

Table 4.10 provides a comparison of average weekly spend for the loyalty card overnight visitors whilst in Cornwall and expenditure by the same customers whilst at home. Differences in store size (which could have an impact on consumer spend) have been accounted for, since it is unrealistic to compare expenditure within a hypermarket with a neighbourhood store. Visitor expenditure in the four study stores is only compared to consumers' home expenditure within other similarly sized stores (based on Sainsbury's in-house classification of their store portfolio). Likewise, consumers' 'home' expenditure during the Christmas period has been excluded from the analysis, since consumers tend to exhibit higher spend during this period.

Visitors' average weekly spend in the Newquay store is around 20% lower than their regular home spend with Sainsbury's in similarly sized stores. It has also been noted (in section 4.4.4) that visitors tend to spend less than local residents in the same store, even when geodemographic characteristics are similar. This suggests that many visitors may be using this resort-centre store for smaller top-up shopping trips, perhaps using other local stores or sources to purchase additional food in line with their usual home consumption habits, or bringing additional food and drink with them from home. By contrast, overnight visitors using the smaller Bude store tend to spend almost £15 more per week than in similar size stores whilst at home. This may be because stores of this size and nature are commonly used for top-up shopping at home, whereas whilst holidaying in the resort many visitors appear to be using this store for a larger shopping trip with a higher spend (perhaps purchasing items that they would not usually purchase at home, or using this smaller store to save travelling to larger stores). The pattern is, however, complex and when considering customers in isolation, there are few clear patterns. Consequently, an understanding of how consumers shop at home during their regular trips to Sainsbury's is not necessarily an indicator of their likely purchasing habits in-store whilst away from home.

Table 4.10 - Overnight visitor spend whilst in Cornwall compared to regular home spend

	Average customer spend per week[9]	
	As an overnight visitor in Cornwall	**Within 'home' stores**
Newquay	£29.66	£36.67
Bude	£35.34	£21.98
Bodmin	£39.87	£43.32
Truro	£56.19	£54.43

Once again, consumers have been considered in terms of their geodemographic status. Table 4.11 compares Newquay overnight visitors' consumption with their usual home consumption at the OAC supergroup level. It is apparent that across all supergroups, the average consumer spends notably more during their 'regular' consumption than they do as a visitor in Newquay. This is especially true for supergroup 3 who appear to have the highest average weekly spend at home (£39.11) (within mid-sized stores), with each loyalty card holder in this group spending an average of £9.11 less per week in the resort compared to at home. Similarly, visitors from supergroup 4 spend an average of £7.47 less per customer per week whilst in Newquay compared to when at home. Since this group also represents the greatest proportion of visitors using loyalty cards in the store, it is clear that the findings identified in Figure 4.10 hold true when the data is disaggregated by OAC Supergroup.

The lower than expected spend among some visitors may suggest that some visitors bring food and drink supplies from home, shop en-route to their destination or exhibit complex patterns of mobility once in the destination, perhaps shopping in multiple stores linked to day trips and visits to attractions some distance from their accommodation. The Nectar card data affords some potential when investigating the spatial patterns of visitor expenditure during and immediately prior to their trip as explored in section 4.6.2.

4.6.2   Additional visitor trip related expenditure

The ability to identify all recorded Nectar card transactions (in Sainsbury's stores) associated with individual consumers allows further analysis of consumption habits associated with overnight visitors. Taking all overnight visitors that had shopped in the Newquay store during the school summer holidays (August, 2010), consumer spend within the Newquay store can be linked to all other transactions carried out by those individual customers using

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[9] This is calculated across the number of weeks that this customer actually shopped in store, not across the entire study period.

their loyalty card during the week of their visit and during the week immediately prior to their trip. This insight can be used to understand more about these consumers' consumption habits associated with a visit to Newquay, even if that expenditure did not take place within the Newquay store.

Table 4.11 - 'Home' and visitor expenditure (within a Sainsbury's store) by OAC supergroup for visitors who shopped in the Newquay store

Supergroup	Home average weekly spend	Average weekly spend in Newquay	Difference (home – Newquay)
1 – Blue collar communities	£34.35	£26.28	£8.07
2 – City Living	£36.55	£30.34	£6.21
3 – Countryside	£39.79	£30.68	£9.11
4 – Prospering Suburbs	£38.98	£31.51	£7.47
5 – Constrained by circumstances	£33.15	£26.47	£6.68
6 - Typical Traits	£36.15	£28.11	£8.04
7 - Multicultural	£37.74	£34.21	£3.53
Average	£36.67	£29.66	£8.07

Table 4.12 outlines the expenditure profiles of three of these overnight visitors that shopped in Newquay. These customers are fairly typical of the range of consumption habits identified, highlighting the complex range of trip related expenditure habits. Customer A, for example, exhibits a far higher spend than usual during their pre-trip shop, which is carried out at home, topping-up twice more whilst in the destination (using both the Newquay and Truro stores). This customer spends considerably more than during their regular consumption and splits this expenditure between stores at home and within the destination. Approximately 40% of the customer sample exhibit habits that are broadly similar, although the exact volume and value of sales varies considerably.

Customer B carries out their pre-trip shop en-route to the destination, shopping in a store close to the M5 motorway, again spending more than in their regular shopping trips with Sainsbury's. In common with Customer A, Customer B also splits their within-destination spend across multiple stores and similar characteristics are exhibited by around 35% of the sample. By contrast, Customer C represents a low-spender within the destination and actually spends slightly less than usual during their pre-trip shop, recording no other transactions during the week of their trip. This customer may therefore have used serviced accommodation, or been hosted by friends and relatives, resulting in a low food spend within

the destination. They may also demonstrate little brand-loyalty whilst away from home, shopping with other retailers en-route or whilst at the destination.

Table 4.12 - Individual customer expenditure profiles for pre-trip and trip related spend.

	Customer A	*Customer B*	*Customer C*
Approximate proportion of customers displaying similar habits[1]	40%	35%	25%
Home location	Greater London	Derby	Hampshire
Average regular weekly home spend (using loyalty card)	£114.01	£58.94	£131.76
Spend during the week prior to their trip	£352.05	£92.83	£126.73
Location of spend prior to trip	Stores in Greater London	Store close to M5 motorway in Somerset	Stores in Hampshire
Spend recorded in Newquay store	£50.54	£51.14	£8.50
Additional spend during trip week	£92.14	£61.60	-
Location of additional spend during trip week	Truro	Truro	-

[1] Based on all overnight visitors that shopped at the Newquay store during summer 2010

Table 4.12 suggests that a proportion of visitors carry out a major food shop en-route to Cornwall or prior to leaving home, in addition to shopping within the destination. It is highly likely that a number of other customers who have not shopped at all with Sainsbury's whilst visiting Cornwall (and thus do not form part of this dataset) may also carry out a major pre-trip food shop at their home store or at a store en-route to Cornwall. This raises an important issue for Sainsbury's to consider. The expenditure outflow associated with visitors that are away from home may in part be offset by the additional pre-trip expenditure, with implications for managing stock levels at this time of year, with additional stock required in the week prior to periods such as bank holidays, where a high number of residents are likely to be away from home. Additionally, if retailers such as Sainsbury's are able to incentivise consumers to stock up on holiday food and drink before leaving home, they can ensure that they tap into visitor demand, even where visitors may be visiting an area not well-served by Sainsbury's stores.

The non-resort based Bodmin and Truro stores also attract considerable additional trip-related spend originating from customers that were recorded as overnight visitors, who appear to be highly mobile once within a destination such as Cornwall, visiting multiple stores. The pattern remains complex, however, and the loyalty card data reveals that many of these visitors routinely record transactions in a number of additional stores some distance from their home address. At the aggregate level, much of this individual level stochastic behaviour is overlooked, and highlights the benefits of using loyalty card data to understand visitor spend, summarised fully in section 4.7.

4.7   Conclusions

This chapter sought to understand the contribution of visitor demand to the seasonal sales variations experienced at Sainsbury's stores in Cornwall. The analysis of store and loyalty card data demonstrates that stores in major Cornish coastal resorts experience a very pronounced seasonal trade pattern. Sales uplift driven by visitor spend is experienced at a number of points throughout the year including Easter, bank holiday weekends and school holidays, with the exact seasonal pattern varying by store, destination and specific product category.

Significant sales uplift driven by visitor demand is experienced at the Bude and Newquay stores during summer, with sales seen to triple at Bude during certain weeks in August 2010. Non-resort based stores in Bodmin and Truro also experience seasonal sales uplift driven by visitor demand, probably due to their proximity to major transport links. Whilst sales to visitors may make up a smaller proportion of overall sales, the larger Truro store, with greater product ranges and higher spend on a customer-by-customer basis, still generates considerable revenue from visitors during the peak-season. The volume and value of visitor demand has been seen to vary on a store-by-store and week-by-week basis, exhibiting considerable variation even during the tourist season.

The Nectar card dataset has allowed actual visitor expenditure to be analysed in order to understand more about the nature of visitor demand and to draw comparisons with local trade. The geodemographic and socio-economic characteristics of consumers at these stores clearly vary by spatial origin, with overnight visitors having a higher propensity to originate from a home postcode within slightly more affluent and higher spending OAC groups. However, at the Newquay and Truro stores, local residents tend to have a higher average weekly spend than visitors with similar characteristics. This suggest that visitors use a more complex range of sources to obtain food and drink, supplementing grocery stores at the destination with eating out, or with food brought from home or purchased elsewhere.

Nonetheless, in the coastal resort of Bude, overnight visitors spend, on average, noticeably more than local residents (and more than they would usually spend in this type of store at home) suggesting that they use this small store for a different type of shopping trip to local

residents. Furthermore, the Bodmin store, located on a major road link through the county, experiences a higher average spend among visitors than local residents. In the absence of significant accommodation provision in the town, this suggests that visitors to other resorts within Cornwall may use stores such as Bodmin and Truro to meet some of their needs. These stores' locations may make them popular choices for visitors, and thus services provided some distance from principal resorts themselves may still benefit from seasonal visitor expenditure.

An understanding of how consumer's expenditure varies away from home is clearly important in identifying and estimating the actual visitor demand available around any given store. The loyalty card data has been a rich and valuable data source for understanding the composition and nature of local resident and external trade, and for Sainsbury's this dataset represents a considerable opportunity to understand more about the nature of external trade in a number of destinations and store types across their portfolio. The value of this dataset could perhaps be enhanced further if individual customer-level transaction data could be broken down by actual products purchased to understand more about specific destination-level grocery spend by visitors. A number of family restaurant chains are also members of the Nectar scheme, allowing Nectar card holders to redeem points towards the cost of food and drink in chains such as Strada and Cafe Rouge. Full linkage across the whole Nectar card dataset to include details of Nectar card usage in these establishments may be able to identify other destination-level food and drink spend by visitors eating out, to understand more about the complex sourcing of food and drink whilst away from home.

This chapter has demonstrated that the investigation of seasonal sales driven by visitor demand is more complex than the analysis of other forms of demand. It is thus essential for all retailers to ensure that their location planning makes full use of all available consumer data to understand the local nature and impact of visitor expenditure. Existing loyalty card data that is held by Sainsbury's has demonstrated that it is possible to build up a detailed spatial and temporal understanding of small-area visitor demand. In particular, an aggregate level focus solely on seasonal trading variations hides the complexity of seasonal sales variations driven by individual consumer expenditure and suggests that traditional approaches to estimate the local level impact of visitor expenditure fail to account for the nature of visitor demand.

The analysis carried out in this chapter strongly suggests that, at a store or local-level, the impact of visitor expenditure cannot be accounted for by simply up-scaling local residential demand in a uniform (spatial) fashion. Differences in visitors' geodemographic and socio-economic characteristics and complex seasonal and spatial variations in the magnitude of visitor demand, mean that estimates of residential demand are unlikely to be a suitable proxy for sales uplift driven by visitors. Consequently, to obtain meaningful revenue estimations, visitor demand should be estimated separately for use in the modelling process to take account of observed differences between the geodemographic and socio-economic

characteristics of visitors and local residents, observed variations in the expenditure habits of visitors relative to local residents and inferred variations in the relative attractiveness of individual stores to residents and visitors.

Chapter 5 seeks to estimate small-area seasonal visitor expenditure for use in location-based modelling and builds upon the insights gained from the loyalty card data and store trading characteristics within this chapter.

Chapter 5: Estimating small-area spatial and seasonal grocery demand in Cornwall

5.1 Introduction

Chapter 4 provided evidence that visitor expenditure is an important driver of seasonal store-level demand uplift in tourist areas such as Cornwall. Grocery stores in the popular coastal resorts of Newquay and Bude were observed to experience considerable seasonal sales fluctuations, with particularly noticeably sales increases during the summer months. Use of consumer loyalty card data suggests that such uplift is driven by visitors, many of whom will be staying nearby in commercial accommodation, hosted by friends and relatives or undertaking day visits to local resorts and attractions. Chapter 2 identified that retailers currently fail to account for the complexities of visitor demand in their location-based decision making, lacking suitable small-area demand estimates. Nonetheless, Chapters 3 and 4 clearly demonstrate that seasonal variations in visitor numbers and their associated expenditure are pronounced, with supply side implications at the store-level (such as periods of overtrading and associated operational difficulties). This chapter seeks to address this weakness by developing a series of small-area seasonal visitor demand estimates for use in store location planning and location-based decision making.

Chapter 3 noted that headline visitor surveys, such as the International Passenger Survey (IPS) (spending by inbound visitors from overseas), the Great Britain Tourism Survey (GBTS) (spending by domestic visitors on overnight breaks in the UK) and the Great Britain Day Visitor Survey (GBDVS) (spending by domestic residents on day trips within the UK) provide robust estimates of visitor numbers at a national or regional level and some indication of the volume of visitor expenditure on key components of the tourism 'product' such as accommodation, transport and shopping. Used in conjunction with economic impact modelling tools such as the 'Cambridge Local Impact Model' (Cambridge Model), these headline figures can be used to generate regional, county or district level assessments of tourisms' economic impact, especially its role in driving expenditure and employment in regional economies.

Whilst useful for identifying headline figures and impacts on broad sectors of the economy, little information can be directly extracted from headline surveys about local level visitor spend or the impact upon specific industries, such as individual retail sectors. It is difficult to identify the impact of visitor spend on food and drink purchased from grocery stores, which is commonly overlooked in both supply and demand side estimates of visitor spend. This form of expenditure is also frequently omitted from smaller scale destination specific surveys of visitor expenditure. The lack of focus on this form of demand is surprising given

that the literature has established the important role of visitors in generating spend in grocery stores (for example see CCC, 2007; Dudding and Ryan, 2000; Timothy, 2005).

Chapter 4 was able to make inferences about visitor demand using data recorded on the supply side. As such, seasonal sales fluctuations were noted and the nature of the demand uplift identified. Chapter 4 clearly identified the importance of visitor demand at a store-level. However, a supply side perspective lacks insight into the specific driving factors responsible for the witnessed demand uplift, since no information is known about characteristics of consumers' visits. Thus, whilst loyalty card data can be used to identify customers who are away from home, it is not possible to identify any other characteristics of that consumers' visit such as the type or location of accommodation used, party size or length of stay. Consequently, the loyalty card data are invaluable in understanding supply side impacts of visitor induced demand but offer limited insight on the demand side.

Local level estimates of visitor spend are thus required in order to fully understand the impact of seasonal visitor expenditure at the level of individual resorts, retail sectors or specific stores. In order to incorporate visitor demand within location-based modelling it is essential to be able to generate these demand side estimations of small-area seasonal visitor expenditure. These demand estimates are built at the OA level and from the 'bottom-up', taking individual accommodation units (in the case of overnight visitors), or specific destinations (in the case of day visitors) as the building block. Where local data is not available, it is supplemented with additional insight from regional and national datasets and modelling tools and disaggregated to the OA level. The OA represents the lowest level of aggregation for small-area household data and is the geographic unit commonly employed by retailers for location-based decision making, including demand estimation and market share analysis.

In order to be used meaningfully in location-based decision making, demand estimates must incorporate all forms of demand, including expenditure by local residents and by visitors who are not staying in commercial accommodation, including day visitors. In order to model the impact of visitor grocery demand at the local level, it must be considered alongside existing residential demand such that the overall demand uplift and impacts on store-level revenue can be considered. An understanding of underlying residential demand is also important since not all expenditure attributable to visitors is directly driven by those visitors themselves, with visitors inducing additional grocery spending among hosts to meet guests' needs.

In common with Chapter 4, Cornwall is again used as the study area due to the clear seasonal impact on store-level trade and the importance of Cornwall as a tourist destination (as outlined in Chapter 4). In common with the supply side data presented in Chapter 4, and for compatibility with occupancy survey data (section 5.3.2), the demand side estimates have been produced for the year 2010. The demand side estimates produced in this chapter are

used extensively throughout Chapters 6 and 7 to develop a modelling framework and demonstrate its utility for location-based decision making. The small-area seasonal demand estimates presented in this chapter incorporate the following forms of demand, each considered in turn within this chapter:

Residential Demand

- Local residents living within the study area and purchasing for their own consumption (section 5.2).

Demand Inflow

- Commuters and workplace populations travelling into the study area purchasing for their own consumption (section 5.2.2).

- Overnight visitors staying in commercial accommodation or their own second home and purchasing for their own consumption (section 5.3).

- Expenditure by small-scale commercial accommodation operators who are purchasing additional groceries for their visitors' consumption (section 5.3.3.4).

- Expenditure by residential households who are hosting visiting friends and relatives and purchasing additional groceries for their visitors' consumption (section 5.4.2).

- Day visitors travelling into the study area for leisure visits and purchasing for their own consumption (section 5.5).

Demand Outflow

- Local residents who usually reside within the study area but are holidaying elsewhere (section 5.2.3).

- Local residents who live within the study area but carry out their grocery shop from an alternative origin such as a workplace or leisure destination (section 5.2.2).

It is the seasonal variations in demand that specifically form the focus of this thesis. Seasonal demand layers are produced for 12 different temporal periods, representing 12 months of the year. A monthly temporal scale is commonly considered appropriate for observing seasonal variations within the tourist sector (see for example Charles-Edwards (2011) for a full discussion). The 12 monthly periods, which are the temporal unit at which accommodation occupancy data are reported (5.3.2), incorporate the peak summer season (driven by the school holiday period in August), the low-season in winter and a number of 'fringe' periods in-between, allowing seasonal variations driven by tourism to be explored fully.

This chapter naturally becomes descriptive in order to outline and fully justify the approach used to create small-area demand estimates. Since little is known about this form of demand at the small-area level, there is no established methodology. The approach used results from an extensive literature review, search for and exploration of potential data sources. Many of these data sources proved unfeasible to use and, for the sake of brevity and clarity, are not discussed within this chapter. The discussion frequently refers the reader back to Chapters 3 and 4 for additional evidence, which are not re-presented in this chapter.

Section 5.2 first considers residential demand and begins with a brief review of data sources and established approaches to estimate expenditure associated with this form of consumer spend. Visitor demand (by accommodation type) is then considered in sections 5.3 and 5.4). Section 5.5 considers day visitors, before the overall seasonal demand estimates themselves are presented and discussed in section 5.6.

5.2   Estimating small-area residential grocery demand

This section seeks to estimate small-area grocery demand originating from residential households, There is no established methodology for this and many retailers use their own in-house techniques based on consumer data, geodemographic indicators and datasets produced commercially by consultancies such as Experian and Pitney Bowes. Pitney Bowes, for example, produces annual retail expenditure estimates for a number of categories of goods at the OA and postal sector level. Their estimates, which form part of a commercial product, combine expenditure rates from the Living Costs and Food Survey (LCF) with census derived and mid-year population estimates (Pitney Bowes, 2011). Most industry estimates of food and drink expenditure are derived using surveyed household level expenditure rates, coupled with small-area household counts and some form of geodemographic data (see for example Birkin *et al.*, 2010a).

5.2.1   Estimating household level grocery demand using the LCF

The LCF is an annual survey undertaken by the Office for National Statistics (ONS). It is part of the Integrated Household Survey (IHS), the biggest pool of social data after the census (ONS, 2011). The LCF was formerly the Expenditure and Food Survey, which itself succeeded the Family Expenditure Survey. It is reported via an annual report titled 'Family Spending' and the LCF itself is often referred to by this name. Results from the 2010 survey have been used here for compatibility with the supply side analysis carried out in Chapter 4.

The 2010 LCF involved a sample of just over 5,000 households (ONS, 2011). Surveyed households completed a diary of expenditure for a two week period, with results weighted to account for the characteristics of all households. The LCF breaks-down household weekly expenditure into 12 expenditure categories, which incorporate food and drink expenditure, used here to estimate small-area grocery demand originating from residential households. The LCF reports household expenditure using an area based geodemographic classification,

recognising that household purchasing power and spending characteristics will be influenced by their socio-economic and geodemographic characteristics. The LCF uses the ONS Output Area Classification (OAC), drawn from census data at the OA level and introduced in Chapter 4. Chapter 4 used loyalty card data to investigate the socio-economic and geodemographic characteristics of local residents purchasing groceries in four Sainsbury's stores in Cornwall. It was noted that residential demand in certain parts of Cornwall was characterised by a number of relatively less-affluent consumers, particularly those from OAC supergroup 6 'Typical Traits' (see Table 4.9 in Chapter 4). It is thus important to take into account the geodemographic characteristics of households when seeking to estimate residential demand in Cornwall.

Alongside food and drink expenditure, additional expenditure on alcoholic drinks purchased from grocery stores is also incorporated, again by OAC group and taken from the LCF. The LCF itself suggests that 49% of consumer expenditure on alcohol is for consumption 'off the premises' (i.e. from supermarkets and off-licences) ranging from an average of £4.26 to £7.60 per household per week. Table 5.1 identifies the LCF expenditure estimates applied here, representing average weekly expenditure at the household level by OAC group. The week is an appropriate unit for considering grocery spend as it represents the temporal scale over which store revenue is recorded and reported. Furthermore, evidence presented by the UK Competition Commission identifies that the most common food shopping frequency exhibited by consumers is weekly, or more frequently, with only 16% of consumers claiming to shop for groceries less frequently than at least once a week (Competition Commission, 2007).

Thus residential grocery demand was estimated at the OA level, using expenditure rates (by OAC group) from the LCF[10], household counts from the 2011 census[11], and the OA level small-area geodemographic classification from the OAC[12]. At the time of writing, an OA

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[10] Table A52

[11] 2011 Census Area Statistics – Table UV053 'Housing Stock'

[12] The bulk of the work contained within this thesis has been carried out prior to the release of 2011 small-area census data. Boundary changes mean that it is not straightforward to combine data from the 2001 and 2011 censuses, yet population increased considerably (by 6.6%) in Cornwall between the 2001 and 2011 censuses. It is thus important to incorporate up-to-date population or household estimates within small-area modelling. Many of the non-census products used (for example drive-time data, Sainsbury's market share and consumer flow data) remain compatible only with the 2001 census geographies. Consequently, modelling has been carried out using 2001 census geographies, but 2011 census counts of households and residential population have been applied. The appendix provides more detail on how data from the two censuses have been combined, taking account of boundary changes.

Table 5.1- Expenditure rates used to estimate household level grocery spend.

All values are in £ per week.

OAC Group	OAC Group Name	Food and Drink	Alcohol spend[13]	Total
1A	Terraced blue collar	47.40	6.57	53.97
1B	Younger blue collar	51.00	6.52	57.52
1C	Older blue collar	50.10	5.73	55.83
2A	Transient communities	42.50	5.78	48.28
2B	Settled in the city	51.20	4.95	56.15
3A	Village life	61.60	6.52	68.12
3B	Agricultural	67.00	6.13	73.13
3C	Accessible countryside	62.00	6.22	68.22
4A	Prospering younger families	61.60	6.22	67.82
4B	Prospering older families	64.20	6.81	71.01
4C	Prospering semis	58.50	5.49	63.99
4D	Thriving suburbs	64.00	7.20	71.20
5A	Senior communities	38.40	5.05	43.45
5B	Older workers	44.70	5.05	49.75
5C	Public housing	42.30	7.89	50.19
6A	Settled households	53.90	5.59	59.49
6B	Least divergent	58.20	5.64	63.84
6C	Young families in terraced homes	48.60	5.49	54.09
6D	Aspiring households	56.70	5.68	62.38
7A	Asian communities	56.80	5.39	62.19
7B	Afro-Caribbean communities	49.60	4.07	53.67

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[13] These values represent 49% of the average weekly alcohol spend to account only for alcohol purchased for consumption 'off-the-premises' and therefore likely to represent spend in grocery stores.

level classification based on 2011 census data has not been produced and the original OAC classification, developed in 2004 (but based on 2001 census data) has been applied. Gale and Longley (2013) note that the OAC may be of limited relevance in areas of the country that have experienced considerable change in the socio-demographic make-up of the population since 2001. Gale and Longley (2013) note that some of the more pronounced change in OA level composition (and thus uncertainty in the OAC itself) is driven by changes in the stock of dwellings rather than simply by population growth. The use of 2011 household counts does account, in part, for these changes in the underlying stock of dwellings.

Using the LCF alongside household counts and their geodemographic status produces a 'static' estimate of expenditure associated with the residential population. This estimate is based on average household spend and assumes that demand does not fluctuate over the course of the year. Loyalty card data has suggested that household level spend increases at certain times of year, such as Christmas and Easter. Whilst incorporating this form of demand uplift is beyond the scope of this thesis, it is important to bear in mind that this form of demand fluctuation can easily be omitted when using average expenditure rates from the LCF.

Based on a comprehensive study of consumer habits, Jackson *et al.* (2006) note that consumer decisions about when and where to shop are increasingly complex and embedded within complex lives and carried out around responsibilities such as childcare and work. As such, residential grocery demand may often originate from workplaces, particularly where a number of residents commute into major settlements on a regular basis for work or leisure purposes. Birkin *et al.* (2010a) and Birkin *et al.* (2004) note that this form of demand should ideally be incorporated when building demand estimates at the small-area level, as outlined in section 5.2.2.

5.2.2   Adjustments to account for workplace inflow and outflow

Recall that the small-area seasonal demand estimates produced here are for use within a SIM (introduced in Chapter 2). The SIM traditionally estimates consumer expenditure flows from residential demand origins to competing stores, which are usually proximate to those origins. In the form that it is applied, the model is unable to account for linked trips, such as grocery shopping linked to commuting. Commuters across Cornwall, who travel into cities such as Truro, may have a range of larger stores available to them near their workplace and may therefore shop on the way home from work. This form of demand does not constitute additional demand; instead it represents a redistribution of demand from the demand zone associated with their home to the demand zone representing their place of work. It is therefore necessary to identify those OAs where there is a net-outflow of commuters and those OAs that experience an inflow of workplace populations and re-distribute demand accordingly.

This redistribution has been achieved by calculating the difference between the OA level daytime population of working age[14] and the usual resident population of the corresponding age group[15], using 2001 census data (since equivalent data from the 2011 census was not available at the time of writing). Demand has been redistributed such that a proportion of the available household demand is re-allocated from residential neighbourhoods to those OAs containing large workplace inflow. There are surprisingly few surveys or data sources that suggest what proportion of grocery shopping is carried out on trips linked to workplaces, yet this information is crucial in order to allocate an appropriate proportion of residential expenditure to workplace origins.

A (now dated) 1994 survey, (East *et al.*, 1994) suggested that 17% of consumers shopped at a store that is easiest to reach from their workplace. In the absence of any further information on workplace shopping habits (which became impossible to source, even with the support of industry contacts), it is assumed that around 17% of household level grocery spend is attached to trips originating from workplaces rather than residential locations. Birkin *et al.* (2010a) acknowledge that the redistribution approach employed here is 'effective to a degree', but note that more complex approaches, which are beyond the scope of this thesis, could seek to allocate a proportion of residential demand to the transport networks used for commuting to and from work. Nonetheless, using this approach, a total of just over £800,000 worth of expenditure per week is redistributed from residential demand origins to workplaces across the modelled study area (Cornwall and west Devon OAs).

Retailers already benefit from methods to incorporate this form of demand redistribution within their own small-area expenditure estimation. Attempts to include it here are acknowledged to be crude. In the absence of access to retailers' existing residential demand estimates, the approach employed here seeks to develop a residential demand layer that can be used as a basis upon which visitor demand estimates can be incorporated, such that store-level revenue and market share can be identified for use across a number of scenarios presented in Chapter 7.

Having estimated OA level residential expenditure (and accounted for workplace inflow and outflow) the resultant demand layer contains no seasonal variation. However, at certain times of year a number of households are likely to be away from home, holidaying elsewhere. Incorporation of this form of seasonal demand fluctuation at the residential household level is considered in section 5.2.3 in order to produce seasonal demand estimates for the residential population.

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[14] 2001 Census Area Statistics Table UV37

[15] 2001 Census Key Statistics Table KS01

5.2.3 Adjustments to account for seasonal and spatial impacts of households holidaying elsewhere

Chapter 4 identified that during school or national holidays many areas of Cornwall must experience a net inflow of people. However, it is important to also account for demand outflow as residents holiday elsewhere. A survey of household level attitudes towards holidays (Mintel, 2013), suggests that households in the more affluent AB social groups show a higher propensity to take a holiday than those in less affluent DE social groups. 84% of household respondents in the AB social groups reporting taking an overnight trip away from home in the previous year, compared to just 51% for those in social group E (Mintel, 2013). The UKTS provides helpful indication of the seasonal pattern of these trips (based on the self-reported month that an individual trip began), broken down by social grade and shown in Figure 5.1.

Since the 2001 census provides information on approximated social grade, households in the study area can be assigned an indicator of social grade, allowing the number of households that are thought to be holidaying elsewhere during any given week to be identified on an OA-by-OA and month-by-month basis. Residential expenditure estimates can be adjusted accordingly to account for the outflow of grocery expenditure associated with households that are away from home, reducing OA level demand in proportion to the number of households thought to be away from home. Using this process, during any given week in August (the month in which up to 14% of holidays begin), almost £500,000 worth of expenditure originating from households in Cornwall is estimated to be 'lost' owing to local households holidaying elsewhere.
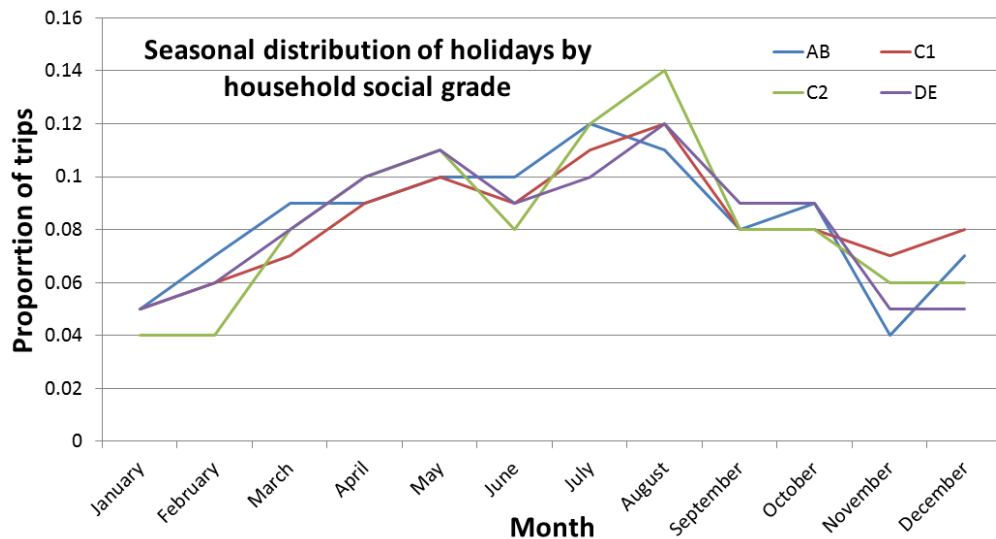
Figure 5.1 - Seasonal distribution of holidays by household social grade

Source: derived from Mintel (2013)

Having accounted for residential demand inflow (driven by workplace population inflow) and outflow (workplace population outflow and households holidaying elsewhere), section 5.2.4 briefly explores seasonal and spatial patterns evident in residential demand.

5.2.4   Seasonal and spatial patterns of residential grocery demand

Following the approach outlined in sections 5.2.1 to 5.2.3 and summarised in Figure 5.2, residential demand for groceries has been estimated at the OA level, accounting for household expenditure by geodemographic status, re-distribution for workplace inflow and outflow, plus seasonal outflow of residential households holidaying elsewhere.

Demand has thus been calculated as:

$$O_i^{kt} = e^k n_i^{kt} \qquad\qquad (5.1)$$

Where:

O_i^{kt} is a measure of the total available expenditure available in zone i by consumer or household type k during seasonal time period t.

e^k is a measure of the average weekly groceries expenditure for consumer or household type k, taken from the living costs and food survey.

n_i^{kt} reflects the number of consumers or households of type k in zone i during time period t and incorporates workplace inflow/outflow and outflow of households holidaying elsewhere.
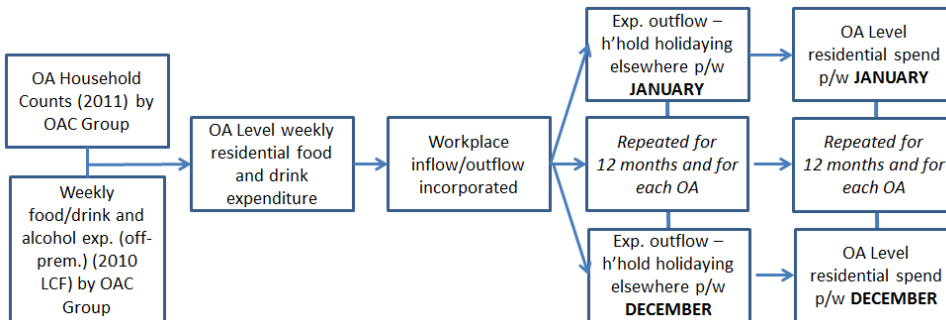
Figure 5.2 - Flowchart to show expenditure estimation process for residential grocery demand

Figure 5.3 shows 52 week average residential household expenditure on groceries for the year 2010, calculated using the methodology described in sections 5.2.1 to 5.2.3, and incorporating workplace inflow and outflow. Expenditure outflow driven by residential households holidaying elsewhere is also incorporated and drives seasonal variations in residential demand. Nonetheless, seasonal variations remain small, since at any one time the maximum number of households thought to be holidaying away from home (in any individual OA) is less than 3% of all households.

A residential grocery expenditure of over £15m per week is available county-wide (based on 52 week average flows), representing an average household spend of just over £63 per week on groceries. Figure 5.3 shows a fairly uniform distribution of residential grocery expenditure at the OA level, in part a result of census OAs having been constructed in order

to maintain a fairly consistent number of households per OA. As such, no clear spatial patterns in residential demand are evident, with differences between OA level spend largely driven by geodemographics and small variations in the total number of households.

Although only mapped in Figure 5.3 (and indeed subsequent figures) for the County of Cornwall, it should be noted that the demand surface (and later supply side) have been modelled for a larger area to encompass demand zones and stores in the neighbouring county of Devon. Birkin et al (2010a) note that customers show no regard for, or even knowledge of, administrative boundaries in their choice of where to shop! Therefore, when modelling consumer flows in east Cornwall, demand 'inflow' to stores in Cornwall from demand originating in west Devon and demand outflow from Cornwall to stores located in west Devon must be considered. This is true particularly in north east Cornwall where the major A30 and A39 road links provide easy access to neighbouring settlements. The presence of a toll bridge on the river Tamar between Plymouth and Torpoint is likely to limit some of the cross border flows in this area, although personal mobility into Plymouth for work and associated linked trips is still likely to have an impact (and has been incorporated within estimations of workplace outflow). By incorporating additional demand and supply outside the area of interest all possible interactions are incorporated.
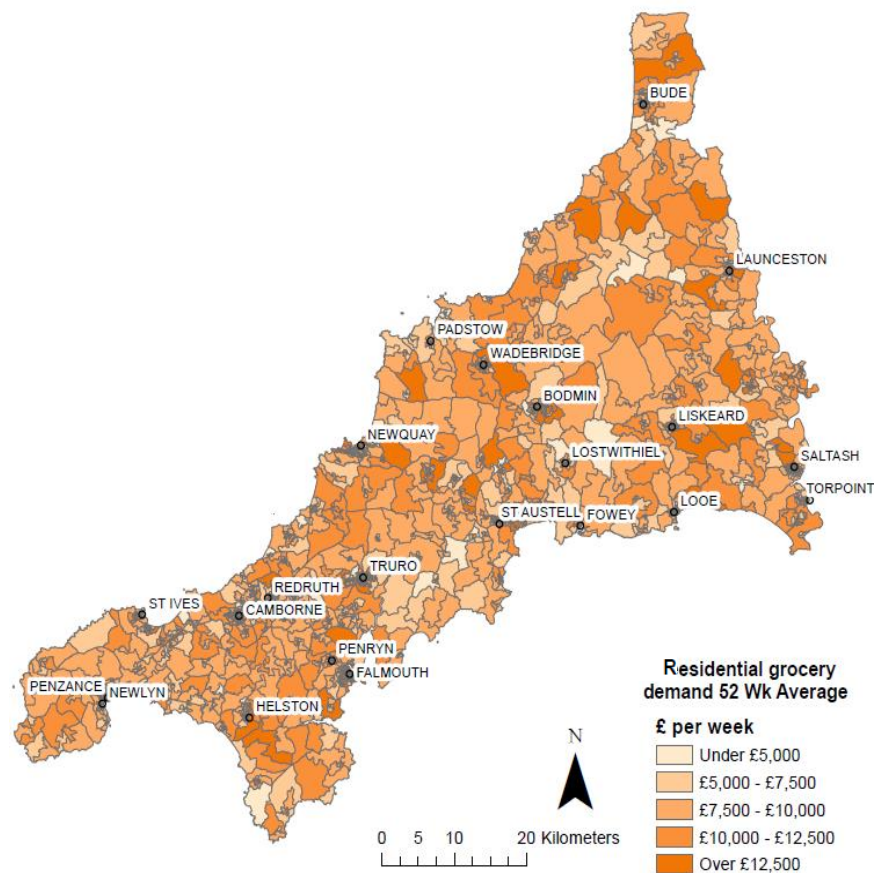
Figure 5.3 - 52 week average (2010) grocery demand derived from residential households

Incorporating workplace expenditure inflow/outflow and residential outflow due to households holidaying elsewhere.

Figure 5.3 is referred to frequently throughout this chapter, since certain forms of visitor demand show a very pronounced spatial pattern, particularly during the peak-season, with clear implications for store location planning. It was noted in Chapter 2 that residential demand is often up-scaled in an attempt to account for estimated demand uplift due to visitor demand. The clear differences between the spatial patterns evident in Figure 5.3, and those explored for visitor demand in sections 5.3 to 5.5 suggest that the use of an up-scale factor is unrealistic (discussed more fully in section 5.6).

5.3 Estimation of small-area seasonal expenditure driven by visitors using commercial accommodation

As highlighted in Chapter 4, store trading data reveals that visitor demand exhibits a clear seasonal pattern, with the volume and value of visitor demand (as recorded at a store-level) peaking during the August school summer holidays and representing a far less significant proportion of store trade during the winter. Chapter 4 identified that the magnitude of visitor demand uplift varies spatially, with certain stores experiencing more pronounced demand uplift during the peak-season, undoubtedly driven by large numbers of visitors staying in accommodation nearby, or the popularity of particular resorts as destinations for day visitors.

Chapter 2 identified that common practice when estimating visitor demand for use in grocery store location planning (as evidenced through planning applications) involves the simple up-scaling of residential demand. A pre-determined factor is often used, and is thought to account for some of the additional expenditure originating from visitors at certain times of the year. Recent applications for new stores or store extensions in Cornwall have employed tourist demand uplift values of 30%, 25% and 15% (API, 2010; API, 2011; API, 2012). This approach is crude and could be misleading as it assumes that the spatial distribution of visitor demand is closely related to the spatial characteristics of residential demand.

As explored throughout this section, certain types of visitor accommodation exhibit a tendency to cluster spatially into large sites where other facilities, such as entertainment and leisure can be provided. This may be particularly true for many forms of self-catering accommodation such as holiday parks and camping and caravanning sites, the largest of which (in Cornwall) has a capacity for almost 2,500 guests, generating an extensive spatial cluster of visitor demand during peak operating periods. Given that such spatial and temporal variations in visitor demand exist, and that these are often unrelated to the spatial distribution and characteristics of residential demand, an alternative approach not reliant on up-scaling of residential demand is required in order to estimate visitor demand for incorporation in location-based modelling. Chapter 2 identified that some location planning teams increasingly seek to incorporate the largest accommodation sites within their demand estimation and spatial modelling, and in part, it is that approach which has informed the development of visitor demand estimates.

Chapter 3 outlined the important role of accommodation in determining visitor grocery expenditure, with those visitors staying overnight in self-catering accommodation exhibiting a propensity to spend more on groceries (given the provision of catering facilities within their accommodation). Throughout this section, accommodation supply and utilisation are used in a 'bottom-up' approach, which first seeks to estimate the stock of available visitor accommodation and its subsequent utilisation, to which expenditure estimates are applied. This approach thus builds on the approach used by the Scarborough Tourism Economic Activity Monitor (STEAM) (see Chapter 3) and recognises the importance of accommodation in determining spend within the local economic impact modelling tools commonly applied in the tourism sector. This approach is also consistent with the approach taken by some location planning teams, by incorporating overnight visitors using their accommodation as a demand origin. However, whereas location planning teams are believed to incorporate them within their residential demand layers, this chapter seeks to generate a separate visitor demand layer, such that seasonal variations can be fully incorporated and handled separately from residential demand.

Chapter 3 outlined the different types of accommodation, broadly defined here as commercial accommodation (incorporating serviced and self-catering accommodation) rented formally, and non-commercial accommodation such as an owner staying within their own second home or with friends and relatives. Section 5.3.1 seeks to briefly outline the spatial distribution of commercial visitor accommodation in Cornwall, before sections 5.3.2 and 5.3.3 apply occupancy and expenditure rates to estimate visitor expenditure associated with visitors staying in all forms of commercial accommodation. Section 5.4 turns attention to visitors staying with friends and relatives or in a second/holiday home and finally section 5.5 considers day visitors.

5.3.1   Commercial accommodation stock

Cornwall boasts a large and well-developed stock of commercial accommodation, including some of the largest and best equipped holiday parks in the UK, plus vast numbers of privately-owned guest houses, B&B and camping accommodation. Whilst the importance of all these forms of accommodation in generating visitor spend and local economic impacts is well understood, there is no comprehensive or complete database of visitor accommodation in Cornwall (or indeed elsewhere in the UK). Ease of entry/exit into this market, and the highly fragmented and seasonal nature of accommodation provision (often dominated by small businesses operating for part of the year) means that even periodic snapshots of provision fail to account for all available accommodation (Johns and Lynch, 2007).

Nonetheless, most local authorities or tourist organisations will maintain some listing of accommodation that is known to them, often through grading schemes or via participation in occupancy surveys or other local initiatives. This section makes use of a comprehensive database of commercial accommodation that was provided by South West Tourism (SWT).

The database contains individual records for all accommodation sites, units and providers that were known to SWT as of February 2011 and had been collated and updated by SWT over a number of years, following regular surveys of accommodation establishments.

SWT was funded by the South West Regional Development Agency (SWRDA) and was responsible for delivering the tourism strategy for the South West. Following the withdrawal of funding to RDAs, South West Tourism ceased operations in March 2011. Some of the functions previously carried out by SWT have been transferred to 'The South West Tourism Alliance' (SWTA), an industry-led consortium of tourism businesses. It is understood that SWTA have not maintained an accommodation database and as such the 2011 snapshot remains the most complete and up-to-date audit of accommodation provision within Cornwall.

The database contains, on an establishment-by-establishment basis, the name, postcode, number of rooms/accommodation units and number of bed spaces. This is in common with the good practice outlined by White (2010a) in guidance to local tourism officials. Unfortunately, the database does not contain occupancy rates or months of the year operating, both recommended as good practice, which would assist considerably in estimating small-area visitor spend. Information on months of operation was thus added during the validation and updating stage, whilst occupancy rates are explored below.

Considerable data cleansing was required before the database could be used for analysis, including updating missing or miscategorised units, adding missing postcodes and amending incomplete details about the number of units, bedrooms and bedspaces through web searches, contact with visitor/tourist information centres and accommodation operators. hotels, guest houses and B&B accommodation are generally easy to identify and verify with almost all having a web presence in the form of their own website, and with listings on major booking and review sites (almost all of which provide details on the number of rooms or bedspaces).

The identification of other forms of self-catering accommodation, such as cottages and apartments, is more challenging and represented a major task due to the number of agencies and web-based listings that exist. Many self-catering units are privately owned and advertised through multiple agencies and therefore avoiding double counting (along with accurately identifying the location of each unit) is a challenging but crucial task. Johns and Lynch (2007) suggest that it is impossible to work through these listings and produce an accurate list of self-catering accommodation and instead they suggest a number of proxies (such as the number of web-based listings) to suggest the overall size of the self-catering provision in any given area. However, since this thesis specifically aims to model small-area demand and subsequent flows of expenditure to stores, accurate locations for each accommodation unit are required. Attempts have therefore been made to produce a comprehensive list of the self-catering provision.

Within the SWT database there are 25 major accommodation agencies, with some hosting over 800 self-catering properties. The effort involved in validation here should not be underestimated, especially given the unwillingness of many agencies and large accommodation operators to provide any detail on their accommodation stock. Validation thus relies on web-listings to be maintained and updated and considerable user input to identify accommodation units listed by multiple agencies and operators. Taking the resort of Newquay as an example, a total of 645 bedspaces were 'missing' from the SWT database, predominantly spread across 10 major apartment developments. Since these developments are geographically proximate, it is anticipated that their exclusion from the database could have resulted in potentially large clusters of visitor expenditure being omitted. A 2005 accommodation report (specific to the Newquay resort), states that new developments such as these are important to the town since "compared to the coaching holiday makers, who spend little outside their hotels, independent holiday makers using the new holiday and residential apartments for self-catering holidays are generally more likely to spend in the local area, whether at supermarket chains or local suppliers" (HIL, 2005, p61).

In spite of the considerable validation carried out, it is inevitable that the accommodation database will be lacking some accommodation units, or that incorrect details regarding operational season and capacity will remain. This is unavoidable given the highly fragmented nature of accommodation provision, lack of compulsory registration and the ease of entry and exit from this sector (especially for self-catering units). The experience of the author suggests that the practicality of carrying out a full validation and updating exercise is very limited, except where considerable resources are available. Nonetheless, following the exhaustive updating carried out, the database was thought to represent the most complete listing of accommodation provision in Cornwall on completion of validation and updating, in May 2011. It is almost impossible to maintain such a database without the support of local tourist organisations and operators, and as such the database has not been maintained since May 2011, and represents a snapshot of provision at that time.

Table 5.2 shows the overall breakdown of the county-wide accommodation stock by type, drawn from the accommodation database. The categories are based on those used by White (2010a) in his guidance to tourism officials operating at the sub-regional and local level (in the UK). Table 5.2 clearly highlights the dominant role of self-catering accommodation (tourist campsites, holiday centres and rented cottage/apartment) in overall provision, collectively representing over 80% of the available bedspaces. The high provision of holiday centres and tourist campsites are likely to meet the demand for family holidays, many of which are seasonal in nature, focussed predominantly around the school summer holidays. A 2010 draft of the Local Planning Framework (Cornwall Council, 2010) expressed concerns that the accommodation stock is narrowly focussed on meeting the needs of self-catering breaks. Table 5.2 suggests that this is true, and in common with the (now dated) Regional

Planning Guidelines for the South West (RPG10) (DTLR, 2001) identifies that hotels, guesthouses and B&Bs make up only 15% of the accommodation provision.

Table 5.2 - Commercial accommodation stock by type, Cornwall

Type of accommodation	Number of units/ bedrooms or pitches	% of total units/ bedrooms or pitches	Number of bedspaces	% of bedspaces
Hotel	7,698	15	17,714	10
Guest Accommodation[16]	4,295	8	9,210	5
Youth hostels	n/a	n/a	1,810	1
Tourist Campsites	18,431	35	57,793	32
Holiday centres and villages, site with static caravans	11,496	22	47,020	26
Rented cottage/apartment	10,773	20	46,190	26
Total	**52,693**	**100**	**179,737**	**100**

As noted in Table 5.2, the accommodation provision is geared heavily towards self-catering forms of accommodation, which, as outlined in Chapter 3, can be expected to generate a higher grocery spend. Figure 5.4 shows the number of self-catering units at the OA level and shows a high degree of spatial clustering in visitor accommodation provision, most notably around resorts on the north coast, including St Ives, Padstow, Bude and Newquay. The high provision around resorts such as Newquay is largely driven by holiday centres and tourist campsites, with some sites, such as Haven's Perran Sands (9km south west of Newquay), catering for around 2,500 guests. Indeed, almost 50,000 bedspaces located within holiday

[16] Bed and breakfast, farmhouse, guest house and inn.

centres are spread across a total of just 98 sites, with an average of over 550 bedspaces per site. This generates large spatial clusters of accommodation provision and associated visitor expenditure at certain times of year. These forms of accommodation also tend to be more seasonal in nature than serviced accommodation, with a number of sites, including the largest in Cornwall (by bedspaces), Haven's Perran Sands, being closed from November to March.
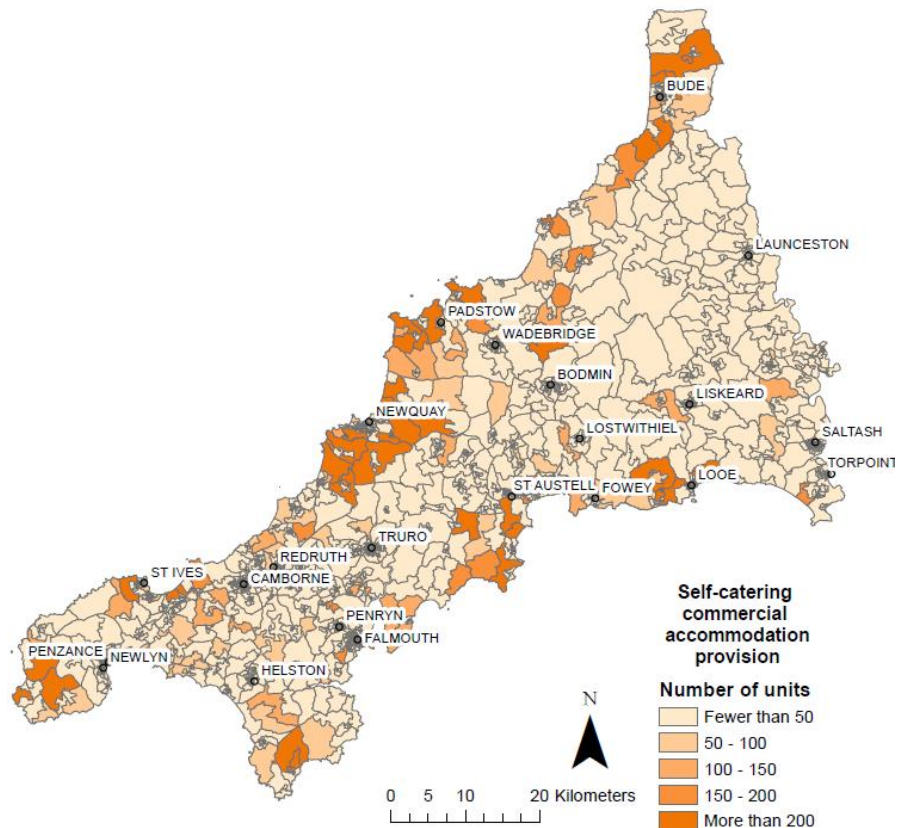
Figure 5.4 - County-wide accommodation provision

> Self-catering units at the OA level. Derived from SWT database (2011), validated and updated by the author.

Table 5.2 identifies that serviced accommodation provision is lower. Less than 10,000 guesthouse and B&B bedspaces are distributed across over 1,000 predominantly small establishments, with 68% of the bedspaces being in establishments with less than 10 bedspaces. However, even though the provision is highly fragmented, these forms of accommodation still tend to be clustered towards major coastal resorts such as Newquay and Bude. As such, commercial accommodation is seen to demonstrate a very different spatial pattern to residential demand, primarily clustered around key coastal destinations, with clear implications for local expenditure and seasonal demand uplift within these areas.

An understanding of the spatial distribution of commercial visitor accommodation, particularly self-catering units, assists greatly in understanding more about the potential distribution of visitor grocery spend. However, when considered in isolation, accommodation provision may not be a reliable indicator of potential visitor expenditure,

since the existence of an accommodation unit does not necessarily imply that visitors will be present or will spend within the local economy. Actual grocery expenditure will be driven by accommodation provision in conjunction with occupancy and expenditure rates, which vary throughout the year and by type of accommodation. As such, expenditure associated with these types of visit will fluctuate during the year as explored in section 5.3.2.

5.3.2 Commercial accommodation occupancy and utilisation

In order to estimate the proportion of the commercial accommodation stock occupied at any given time of year, published occupancy rates can be used. Occupancy rates are readily available at the regional (South West) or county (Cornwall) level for all forms of serviced and self-catering accommodation (excluding hostel accommodation). As noted in Chapter 3, occupancy surveys remain the only meaningful source of data on accommodation utilisation. Occupancy rates used to estimate commercial accommodation utilisation for this thesis are shown in Table 5.3, and have been derived from a series of reports produced by South West Tourism and Visit Cornwall, using their recruited sample of visitor accommodation providers. It is clear that during the peak summer season (August) all forms of accommodation experience high occupancy rates, with 94% of all available units occupied. Figure 5.5 demonstrates the spatial patterns of accommodation utilisation at the OA level taking occupancy rates into account.

In August 2010 (which represents the peak-season), high occupancy rates across all forms of accommodation result in many accommodation sites operating close to capacity. The impact, as shown on Figure 5.5, is that large spatial clusters of occupied visitor accommodation become apparent, especially on the north coast of Cornwall, in a band of OAs stretching from Perranporth (south west of Newquay) to Bude (incorporating the resorts of Newquay and Padstow). A similar pattern is seen on parts of the south coast, notably around Penzance and between Falmouth and Looe. In January, by contrast, the overall number of occupied units is far lower, since much of the touring and holiday park provision is closed at that time of year. Those that are open achieve low occupancy.

Having outlined the seasonal patterns of commercial accommodation utilisation, section 5.3.3 now considers its impact on small-area visitor grocery spend, before considering other forms of accommodation in section 5.4.

5.3.3 Commercial accommodation visitor expenditure

This section aims to estimate small-area visitor grocery expenditure associated with commercial accommodation. Expenditure is driven by the occupancy patterns identified in section 5.3.2. Available weekly expenditure is calculated by multiplying the accommodation provision (by type) by the given occupancy and expenditure rates and summed on an OA-by-OA basis across all accommodation types (Figure 5.6). All rates used refer to weekly grocery expenditure and, with occupancy rates available on a monthly basis, average weekly visitor grocery expenditure can be calculated separately for each month.

Table 5.3 - Accommodation occupancy rates for Cornwall (2010)

	Hotel	Guest Accom	Youth Hostels	Tourist Camp-sites	Holiday centres/ villages[17]	Rented cottage/ apartment
Month	% of rooms occupied	% of rooms occupied	% of bedspaces occupied[18]	% of pitches occupied	% of units occupied	% of units occupied
Jan	28	25	25	8	12	12
Feb	40	35	35	12	29	29
Mar	43	38	38	9	29	29
Apr	56	48	48	44	60	60
May	62	57	57	64	62	62
Jun	71	67	67	70	67	67
Jul	75	72	72	76	77	77
Aug	79	74	74	97	94	94
Sept	69	68	68	46	82	82
Oct	54	51	51	34	42	42
Nov	33	26	26	13	12	12
Dec	31	22	22	19	24	24

Grocery expenditure rates for visitors using commercial accommodation are difficult to obtain due to the broad range of accommodation provision within this sector (which includes self-catering lodges and static caravans located on holiday parks, alongside holiday cottages and apartments in residential areas, plus all forms of serviced accommodation) and a lack of previous research. The provision and range of commercial accommodation is so varied (and in some cases destination-specific) that it becomes almost impossible to generalise about the expenditure habits associated with visitors. Each form of accommodation and destination will attract different demand segments, at different times of the year, each with their own expenditure habits, as noted in Chapter 3. This presents a unique challenge in that the characteristics, preferences and purchasing power of consumers using rented accommodation change frequently, unlike residential demand which tends to remain more static.

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[17] Includes sites with static caravans.

[18] Rates listed for 'guest accommodation' have been used here
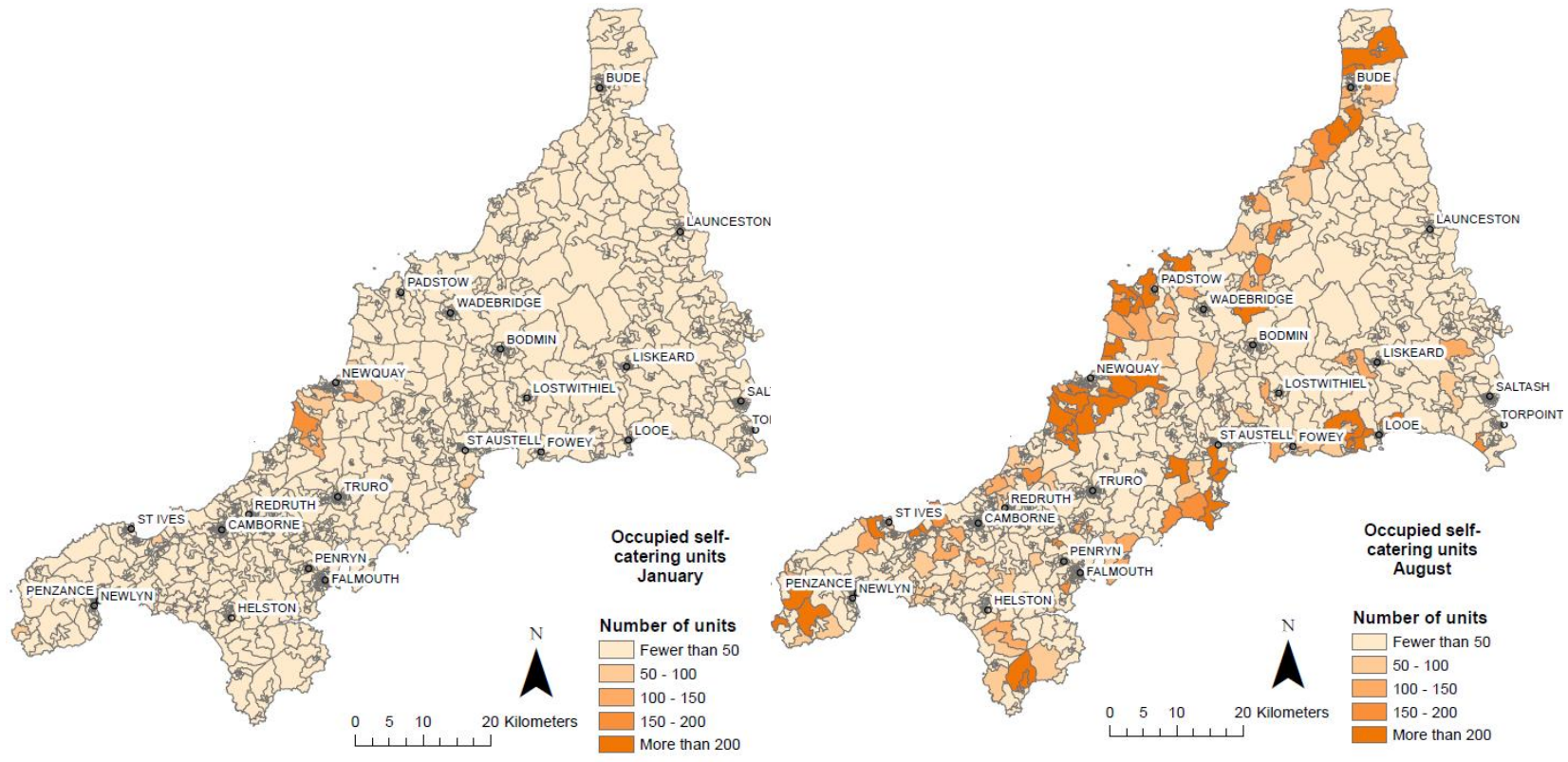
Figure 5.5 - Self-catering accommodation occupancy in a) January 2010 and b) August 2010

Notwithstanding these points, in developing modelling tools that can be applied across coastal resorts with highly seasonal demand, it is important to be able to make inferences about the broad expenditure habits associated with visitors using commercial accommodation, applicable to many types of visitor, trip purpose or length of stay. To estimate expenditure associated with specific types of accommodation, generalisations will therefore need to be made. Headline visitor surveys such as the IPS and UKTS are not helpful here, since they do not collect information on visitors' grocery expenditure habits.

Alternative industry surveys have been used to obtain average grocery expenditure rates for visitors using each form of commercial accommodation. In all cases, identified rates have been converted to average weekly expenditure per party. This is important since the expenditure estimation needs to provide weekly demand estimates for compatibility with residential expenditure estimates and existing store location planning. Furthermore, the unit used for accommodation supply was in terms of units and/or rooms (commonly occupied by a 'party' or group of visitors travelling together) rather than bedspaces (commonly occupied by individuals, who form part of a party).
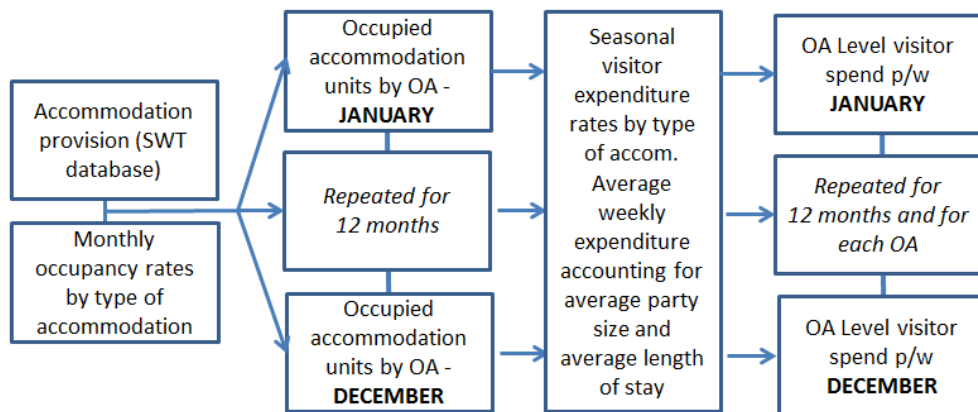
Figure 5.6 - Flowchart to illustrate 'bottom-up' approach to estimate visitor expenditure

Applying expenditure rates per unit allows average party sizes to be taken into account, recognising that not all bed-spaces within a given unit will necessarily be occupied. Since party size is known to increase in Cornwall during the summer months, expenditure rates for the peak summer season (June – August) are higher to reflect the impact of larger party sizes on likely grocery spend. Whilst it is acknowledged that these rates will not be applicable for each party/accommodation unit, they are generally representative of the type of expenditure habits of visitors using these forms of accommodation. The following sub-sections outline the expenditure rates used, which are then summarised in Table 5.4 (Section 5.3.4).

5.3.3.1   Tourist campsites

As outlined in Chapter 3, visitor expenditure data for this sector are traditionally difficult to obtain, in part a result of the fragmented and variable nature of camping and caravanning

provision, made up of a number of small, private operators coupled with large commercial sites operated by organisations such as the Camping and Caravanning Club (CCC). The expenditure estimates used here are based upon the findings of a detailed national survey undertaken by the CCC and introduced in Chapter 3. Excluding site fees themselves, the survey identified that the highest spend by their visitors was on supermarket provisions, closely followed by expenditure on other sources of food and drink, including eating in local pubs and restaurants. Overall expenditure on groceries per-pitch per-week was £66.08, but this was seen to vary by type of unit. In the absence of alternative data, the CCC expenditure rate of £78.23 per week for families during the summer has been applied for the June to August peak-season, whilst the average at £66.08 per-party per-week has been applied at all other times of year, representing the smaller party size outside the peak summer season.

5.3.3.2   Holiday centres and villages including sites with static caravans

These large parks tend to incorporate a variety of accommodation, much of which will be rented on a short-term basis to visitors, whilst some may also be privately owned and used in a similar form to a second home or as a semi-permanent residence. The facilities provided vary considerably, with some large parks providing on site entertainment and leisure facilities, and other services such as grocery stores and catering facilities. This means that holiday makers may spend little time outside the site and need to spend little on groceries within local stores. Others will provide very basic facilities, meaning that visitors spend little time on-site and undertake most of their expenditure in the local community.

The British Holiday and Home Parks Association (BH&HPA) have carried out a range of comprehensive studies to demonstrate the positive economic impact of these parks on local economies (e.g. BH&HPA, 2012). In one such study, a face-to-face survey of 517 visitors to 21 parks was used to understand more about expenditure in the local community by visitors. The survey identified that visitors spent an average of £98 per trip (equating to £79.76 per week in the summer and £71.14 at other times of year after accounting for average trip length and party size) on 'food and drink for self-catering' purchased off-park (therefore excluding purchases from an on-site convenience store). In the absence of further survey data, this value will be employed here.

5.3.3.3   Rented cottage/apartment

There is an absence of studies within either the academic literature or the industry itself that examine, via a robust and representative sample, the grocery expenditure patterns of visitors using any form of rental cottages/apartments. One of the most detailed existing studies was carried out by Mottiar (2006) in a localised area within County Wexford, Ireland. Her survey suggested that those in rented self-catering accommodation spend an average of €24.24 per party per day on groceries. Based on the exchange rates at the time of the survey (2001), this equates to expenditure of around £15 per party/unit per day on groceries. However, Mottiar's study does not include details on party size or length of stay, and the expenditure may be

determined by characteristics of the destination itself which makes it difficult to directly apply expenditure from a localised study such as this to the whole of Cornwall.

Nonetheless, and in the absence of any more robust insight, the rates identified by Mottiar can be used as a guide for estimating expenditure associated with self-catering accommodation, coupled with insight taken from a series of surveys of visitors to Newquay (undertaken in 2004) and to Cornwall (undertaken in 2008/9). These surveys found that visitors self-reported expenditure on all forms of shopping, including 'sweets, drinks, food (not consumed in a restaurant, cafe or pub) and other purchases' ranged from £8.63 to £9.51 per person per day (South West Tourism, 2005b; VisitCornwall, 2009). Assuming that half of this expenditure was on some form of groceries (in the absence of any further sub-division of expenditure), and an average party size of 3.24 people during the peak summer season, falling to 2.89 at other times of year (VisitCornwall, 2009), it is suggested that these visitors spend up to £15.40 per unit/party per day on groceries, in the summer (and £13.74 at other times of year) equating to £107.80 (£96.18) per week. This is broadly in line with Mottiar's findings and is thus employed within this analysis.

5.3.3.4   Serviced accommodation

Serviced accommodation incorporates hotel, B&B, guest house and hostel accommodation, which, with the exception of the latter, are not commonly associated with generating considerable grocery spend, since catering facilities for guests are generally not provided. Almost all of these accommodation operators provide breakfast and some also provide an evening meal for guests. Consequently, purchases in grocery stores by these guests are likely to amount to little more than snack food, newspapers and similar incidental purchases. Very limited information exists on this form of consumption by visitors and these products can be purchased from a range of other stores. As such, expenditure directly attributable to guests using serviced accommodation has not been incorporated within the modelling.

Nonetheless, it is inevitable that many smaller accommodation operators may source food and drink for guest consumption from their local supermarket. Owners of small B&B or guesthouse accommodation may purchase food and drink for guest breakfasts alongside their own food shop in their local supermarket, in order to save a trip to local wholesalers. This form of induced visitor food and drink expenditure, carried out by hosts, is not commonly surveyed or assessed in studies of tourism's local economic impact. Following a comprehensive search, the author can find no direct reference to this form of expenditure within any such study. However, many traditional studies of tourism's economic impact (for example see Frechtling, 2006) are based on multiplier analysis. Within these studies, rates of expenditure leakage are commonly lower for locally owned B&B or guest house accommodation, suggesting that inputs are likely to be sourced locally, thus generating induced visitor spending in the local economy. In the absence of existing studies, a survey of local serviced accommodation operators (within the resort of Newquay) was carried out by

the author in November/December 2011, seeking to obtain evidence that this form of induced demand did exist, and to quantify its value, such that it could be applied across the serviced accommodation stock.

A short questionnaire was sent to 139 serviced accommodation providers, representing all serviced accommodation in the resort of Newquay. In spite of three follow up emails, only nine responses were received. The responses clearly identified that guest house and B&B accommodation (representing 66% of responses) use a range of sources for food and drink inputs, with at least half purchasing from local supermarkets. Given the very low response rate, and huge variations in spend reported (from £0.91 per guest per night to £4.50 per guest per night), it has not been possible to apply these rates to the commercial accommodation stock.

However, Chapter 8 carries out similar demand estimation for selected districts in Kent where, with the support of the local tourist organisation, a similar survey was undertaken, generating a higher response rate and expenditure rates that could be applied. Full details of the web-based survey and it's respondents is provided within Chapter 8 and based on the surveyed results, an induced expenditure of £1.95 per guest or (assuming double occupancy) £27.30 per occupied room per week has been used to calculate induced visitor spend by B&B and guest house owners for use in demand estimation.

5.3.4 Seasonal and spatial patterns of visitor expenditure associated with commercial accommodation.

Table 5.4 summarises the expenditure rates applied to the commercial accommodation stock in order to estimate OA level expenditure associated with visitors. The seasonal and spatial patterns of visitor expenditure derived from visitors using commercial accommodation are shown in Figure 5.7. Figure 5.7 clearly identifies the considerable difference between available expenditure in the low-season (January) compared to the peak-season (August), with clear spatial clusters of visitor expenditure in August, especially in coastal locations such as Newquay, Padstow and Bude.

Table 5.4 - Expenditure rates applied to estimate visitor expenditure driven by utilisation of commercial accommodation

	Low/Fringe Season *(Sept-May)*	*Peak-Season* *(June-Aug)*
Tourist Campsites	£66.08	£78.23
Holiday centres and villages	£71.14	£79.76
Rented cottage/apartment	£96.18	£107.80
Hotel/guest accommodation	£27.30	£27.30

This section has outlined seasonal and spatial patterns of visitor expenditure associated with visitors using highly seasonal forms of commercial accommodation. However, visitor demand is also driven by visitors staying with friends and relatives (VFR) that reside within the local area, and by owners of second homes/holiday homes within the local area. Visitors using these forms of accommodation tend to have different expenditure and consumption habits than visitors using other types of accommodation, as explored in section 5.4

5.4 Visitor expenditure associated with non-commercial accommodation.

These visits involve alternative forms of accommodation, either in the form of owners using a secondary dwelling (which is occupied primarily for holiday purposes) or being hosted with friends and relatives. Since these visitors are not using commercial accommodation, they tend to have a lower expenditure outlay on accommodation (though second home owners have considerable financial obligations to the property). This often results in assumptions that these forms of visitor are less 'valuable' to a destination, generating limited expenditure. As outlined in Chapter 3, these forms of accommodation generate considerable additional spend in the local community (for example see Backer, 2007; Bischoff and Koenig-Lewis, 2007; McKercher, 1995; Seaton and Palmer, 1997; Spindt and Weiss, 2009; The Tourism Company, 2011; WTO and ETC, 2007). Nonetheless, this form of visitor expenditure is difficult to model, since the accommodation stock and utilisation patterns are complex and hard to identify as outlined in the following subsections, beginning with second/holiday homes.

5.4.1 Visitors staying in second/holiday homes.

Although the literature makes reference to a number of methods for collecting data on second home ownership (e.g. census, Survey of English Housing and Council Tax data) (see Hall and Müller, 2004; National Housing and Planning Advice Unit *et al.*, 2008; South Lakeland District Council *et al.*, Undated), estimating actual numbers of second homes (and subsequently their seasonal patterns of utilisation) is difficult and not routinely part of local level data collection. However, there is a growing interest in local impacts of second home ownership and the 2011 census included a specific question to determine ownership of second homes. However, this dataset was not available at the time of analysis.

The 2001 census provided OA level counts of all dwellings where the usual resident was known to have a permanent address elsewhere. Across Cornwall, these counts suggested a total of almost 10,500 units classed as a second/holiday home[19] at that time. A more comprehensive and timely source of data is council tax data (Wyatt, 2008), based on counts

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[19] Table UV53 (Housing Stock)
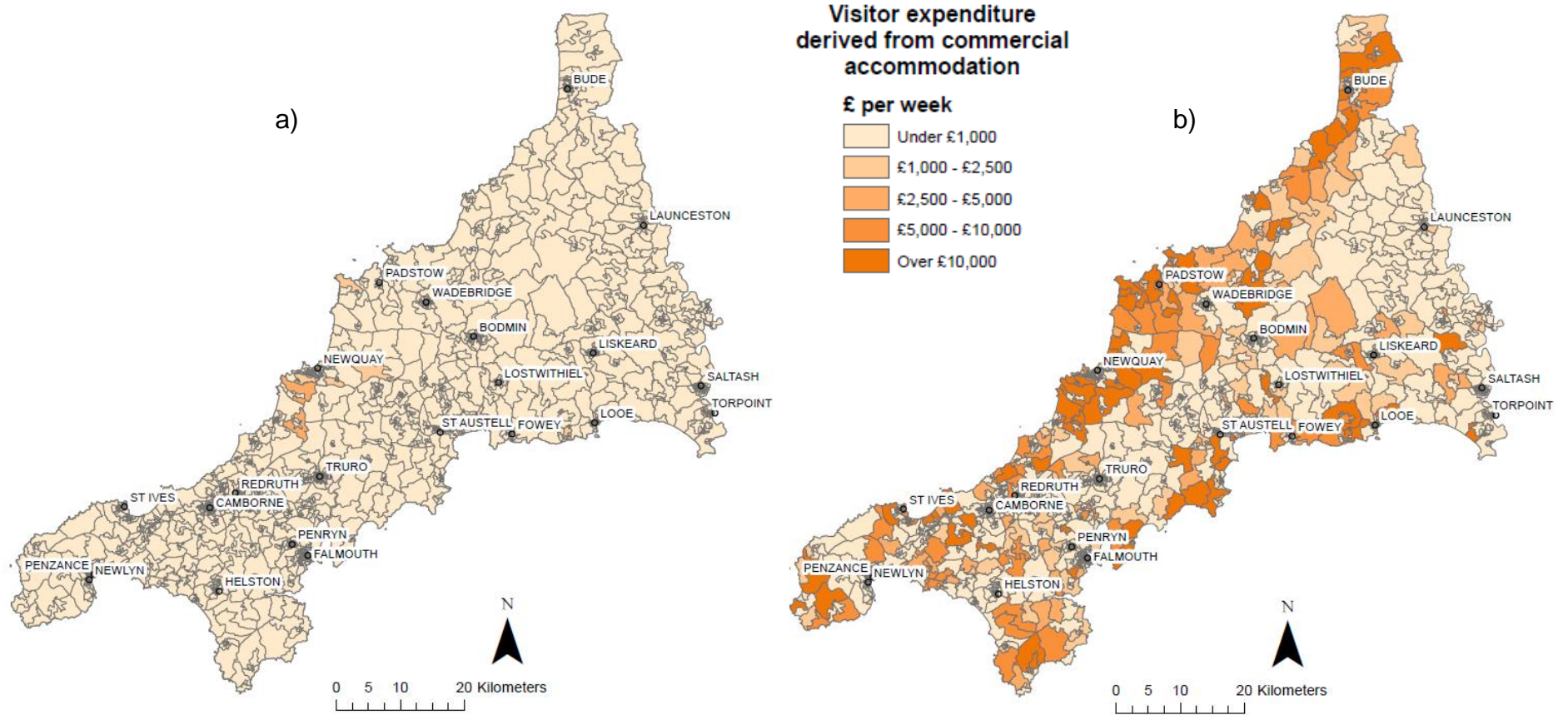
Figure 5.7 - Seasonal and spatial patterns of visitor expenditure driven by commercial accommodation usage in a) January, and b) August. Weekly expenditure is shown at the OA level.

submitted by each local authority on an annual basis using a standardised reporting procedure known as CTB1. Local authorities are often unwilling or unable to release this information at small-area geographies, yet Council Tax data supplied for a parliamentary answer (National Housing and Planning Advice Unit *et al.*, 2008) suggested that 13,040 units, or 5.4% of the housing stock in Cornwall was recognised as a second home. Following an information request to Cornwall Council by the author, limited information on overall numbers of second home units has been provided, at a middle layer super output area (MSOA) level (within Cornwall these contain an average of 2,936 households), representing 2008 data.

The Cornwall council second home records indicate a total county-wide supply of over 14,000 second home units. To incorporate second home ownership within the expenditure estimation it is necessary to make inferences about the distribution of these second home units at the OA level. GeoConvert[20] (part of the ESRC census programme) was used to re-sample the MSOA level second home data to the OA level. GeoConvert disaggregates the second home counts from MSOA level to the OAs that are nested within them, weighted by OA population. This approach provides an estimate of the number of second homes in each OA, making use of counts obtained at the lowest level of aggregation for which Cornwall Council were willing to release data, and allows expenditure and occupancy rates to be applied in common with other forms of accommodation.

The second home units identified by Cornwall Council appeared to show some spatial clustering towards popular resorts on the north coast of Cornwall, especially between Padstow and Bude, and also around Fowey and Looe on the south coast. The high concentration of second home units near Padstow can be clearly seen on Figure **5.8**, containing over 1,000 second home units and representing 36% of the housing stock within this area. It is inevitable that the high number of second home units in this area will have an impact on local services, with demand likely to fluctuate at different times of the year, boosted by the influx of second home owners.

As non-commercial accommodation, second home units are not part of occupancy surveys and understanding occupancy and usage patterns is tricky. Nonetheless, the importance of this form of accommodation in determining grocery demand in some areas (such as Padstow) should not be underestimated and it is important therefore to make some observations about the likely utilisation of these units at different times of the year. Following an exhaustive search of the academic and industry literature and datasets, with support from tourist industry contacts, it was concluded that no established methodology exists to identify second home utilisation at the local level.

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[20] http://geoconvert.mimas.ac.uk/

Second home usage varies considerably, with some owners using their second home most weekends and holidays, whereas others may lie empty for much of the year (Muller, 2004), or may be rented informally (to friends and relatives) or formally (to the public) as part of the rented cottage/apartment accommodation stock. For the analysis which follows, and in the absence of any more insightful data, it has been assumed that second home utilisation follows a similar pattern to rented cottage/apartment occupancy rates; that is, utilisation will be higher during the peak tourist season, no doubt driven by the better weather and availability of resort level facilities and activities during the peak-season.
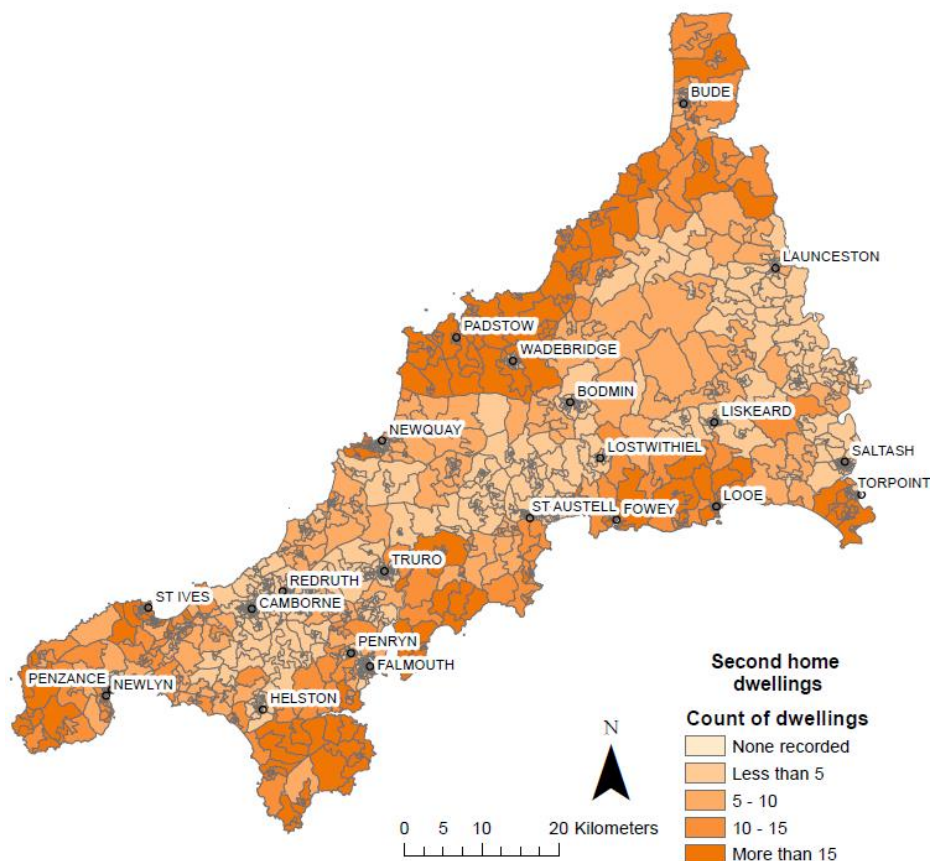
Figure 5.8 - Second home units shown at the OA Level

> Based on disaggregation of 2010 MSOA level council tax data supplied by Cornwall Council

Once again there is an absence of studies within the literature that attempt to identify grocery expenditure by second home owners, which is itself complex and may reflect different usage patterns. As noted with examples in Chapter 3, some second home owners may bring groceries with them from home, whereas, by contrast, others may purchase heavily in the local community. It is not unreasonable to suggest that overall expenditure may be slightly lower than for rental accommodation, since home-owners can keep their dwelling well-stocked with everyday food and drink items and will not need to purchase these staple items on every visit (Quinn, 2010).

Consequently, a grocery expenditure value of £78.55 per property per week has been used. This has been derived from the LCF (2010 data) (ONS, 2011). This value represents the average weekly household expenditure on food and drink by households with the highest gross income (top 20%) since the LCF itself, supported by broader evidence (e.g. National Housing and Planning Advice Unit *et al.*, 2008) suggests that these income groups are far more likely to record household expenditure associated with ownership of a secondary dwelling. As such, this approach assumes that the owners of second home units are likely to exhibit grocery consumption habits whist using their second home unit that are similar to their habits at home.

The expenditure associated with second home owners is incorporated in the outputs shown in Section 5.6. Section 5.4.2 now considers expenditure associated with visitors hosted by friends or relatives.

5.4.2 Visits hosted by friends and relatives

This form of visitor spend has traditionally been overlooked and under-researched as it has often been assumed that their expenditures are low, since they have little outlay on accommodation and food and drink, which are often provided by hosts (Seaton and Palmer, 1997). Nonetheless, it is noted that the 'hidden multiplier effect' (Meis *et al.*, 1995), in the form of additional expenditure incurred by hosts in providing food, drink and entertainment for guests generates additional local expenditure (see Chapter 3 for more detail).

Chapter 3 identified that visitors on VFR trips tend to undertake shorter breaks distributed more evenly across the year, with less evidence of seasonal peaks than some other forms of tourism. Likewise, given that these forms of visit are driven by the underlying housing stock and residential population distribution (as hosts), these visits may also show less tendency to be clustered around particular resorts, where commercial accommodation exists. Consequently, inclusion of expenditure associated with these visitors is important for fully understanding seasonal and spatial patterns of non-residential demand.

Estimating the number of visits to friends and relatives is tricky since this form of accommodation is not uniquely identifiable as a distinct subset of the housing or accommodation supply. Unlike commercial accommodation, it is therefore not possible to build from the 'bottom-up' (i.e. identify stock and then apply utilisation and expenditure rates). Instead a 'top-down' approach is required, whereby inferences are made about the total number of trips and associated expenditure across the study area, which are then distributed across the possible stock of hosts in order to identify a likely spatial and temporal distribution for these visits.

In the absence of suitable local level insight, county-wide data is drawn from existing economic assessments of tourism. Principally a detailed economic impact assessment of the volume and value of tourism in the South West is used. The survey (South West Tourism, 2010d) pulls together a wealth of data and evidence which would be impossible to access

any other way, drawing on outputs from the Cambridge Model (Chapter 3), which is commonly applied in the UK tourist industry for studies of local economic impact. Estimates of local tourist activity from the Cambridge Model are used here to identify the overall host spend for VFR trips, with inferences then made about seasonal and spatial distribution (Figure 5.9). UKTS data is used to distribute the expenditure seasonally, and the underlying housing supply allows disaggregation at the OA level taking account of the housing stock.
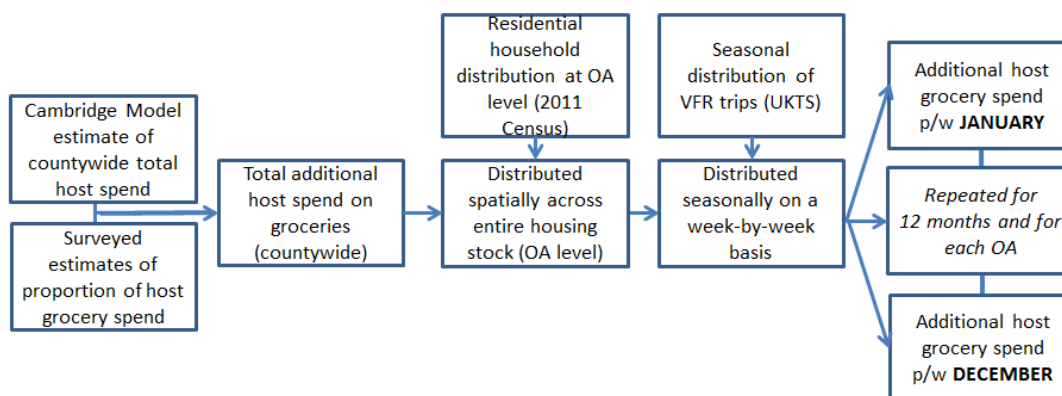
Figure 5.9 - Flowchart to illustrate process to estimate seasonal and spatial distribution of host expenditure

Within the Cambridge Model, overall numbers of VFR trips and associated spend have been estimated using regional data from the UKTS, IPS and ELVS[21], and constrained by any known sub-regional or county data. The latest results for Cornwall obtained from the Cambridge Model (which uses 2008 data) identifies a total additional spend by hosts of just over £40.3m per year. This incorporates both day and overnight visitors and is not disaggregated further. Based on evidence from Chapter 3 (ETC, 2002), assuming that 26% of this is spent on additional groceries, there is an additional £10.5m worth of groceries expenditure available county-wide. This has been distributed equally across the entire housing stock, such that, on an OA-by-OA basis, overall additional grocery spend by hosts can be identified.

Given the seasonal distribution of VFR trips (based on their start month, drawn from regional GBDVS data) (Figure 5.10), which is less pronounced than for other forms of demand, the total available expenditure can be distributed seasonally across the year and calculated on a weekly basis (for compatibility with other input data for the demand layers).

Distributing total recorded VFR expenditure across the housing stock, and then seasonally by month of trip, gives rise to seasonal and spatial patterns of VFR host expenditure associated with VFR visitors (both day and overnight) shown on Figure 5.11. It is clear that the spatial pattern is driven by underlying residential demand, with host spend distributed across the study area, with an absence of spatial clusters around major resorts. The overall magnitude,

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[21] England Leisure Visits Survey, now replaced with the GBDVS.

and relative difference between January and August, is also far less pronounced than for expenditure driven by commercial accommodation. As such, this form of expenditure is less likely to be a major driver of the pronounced seasonal sales peaks at stores in coastal resorts, but instead represent a background overall sales uplift, in part negating the impact of expenditure outflow associated with households holidaying elsewhere.
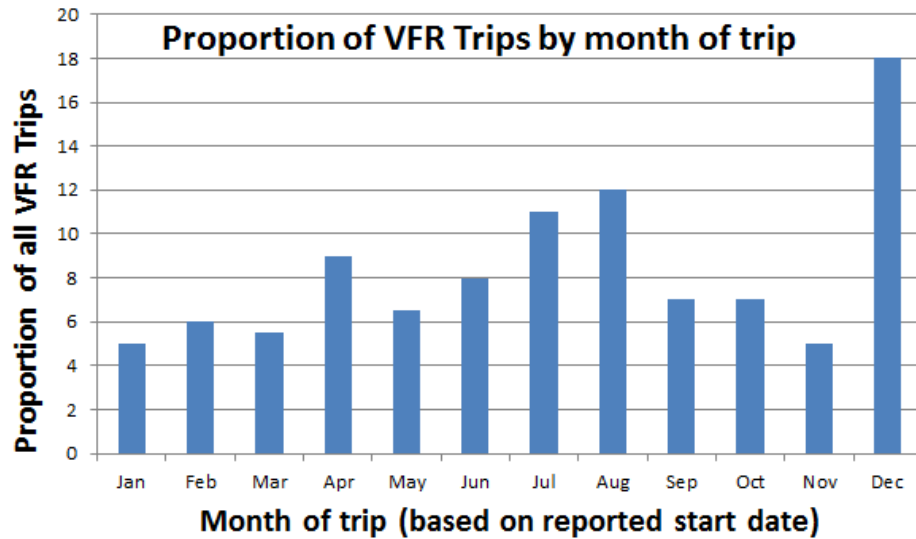
Figure 5.10 - Seasonal distribution of VFR trips by self-reported month trip started.

Derived from data (relating to 2011) within table 4.1.3, GBDVS (VisitEngland, 2012)

In Chapter 8, where district level data is available for a subsequent study area (Kent), VFR expenditure is reported at the district level and an additional seasonal distribution is incorporated for student populations. Such data is not available for Cornwall. Nonetheless, the county-wide expenditure estimates available from the Cambridge Model have formed an important tool for estimating seasonal and spatial demand uplift associated with VFR tourism. Section 5.5 now turns attention to demand uplift associated with day visitors.

5.5 Grocery demand driven by day visitors

Day visitors may also contribute to the store-level grocery demand uplift. By definition, these visitors are making a trip from home (or from accommodation elsewhere), and are not associated with an overnight stay in the destination. As such, their expenditure is lower, in part driven by their shorter length of stay (thus less food and drink is required), the ease of bringing food or drink from home and a higher propensity to eat out (Downward and Lumsdon, 2000; 2003).

As outlined in Chapter 3, the 2011 and 2012 GBDVSs provide the most timely and comprehensive estimates of numbers and seasonal distributions of day trip visitors. Since this survey was not introduced in 2010, data relating to 2011 is used here and suggests that a total of 23.6m day visits were undertaken in Cornwall in 2011. Whilst this does not
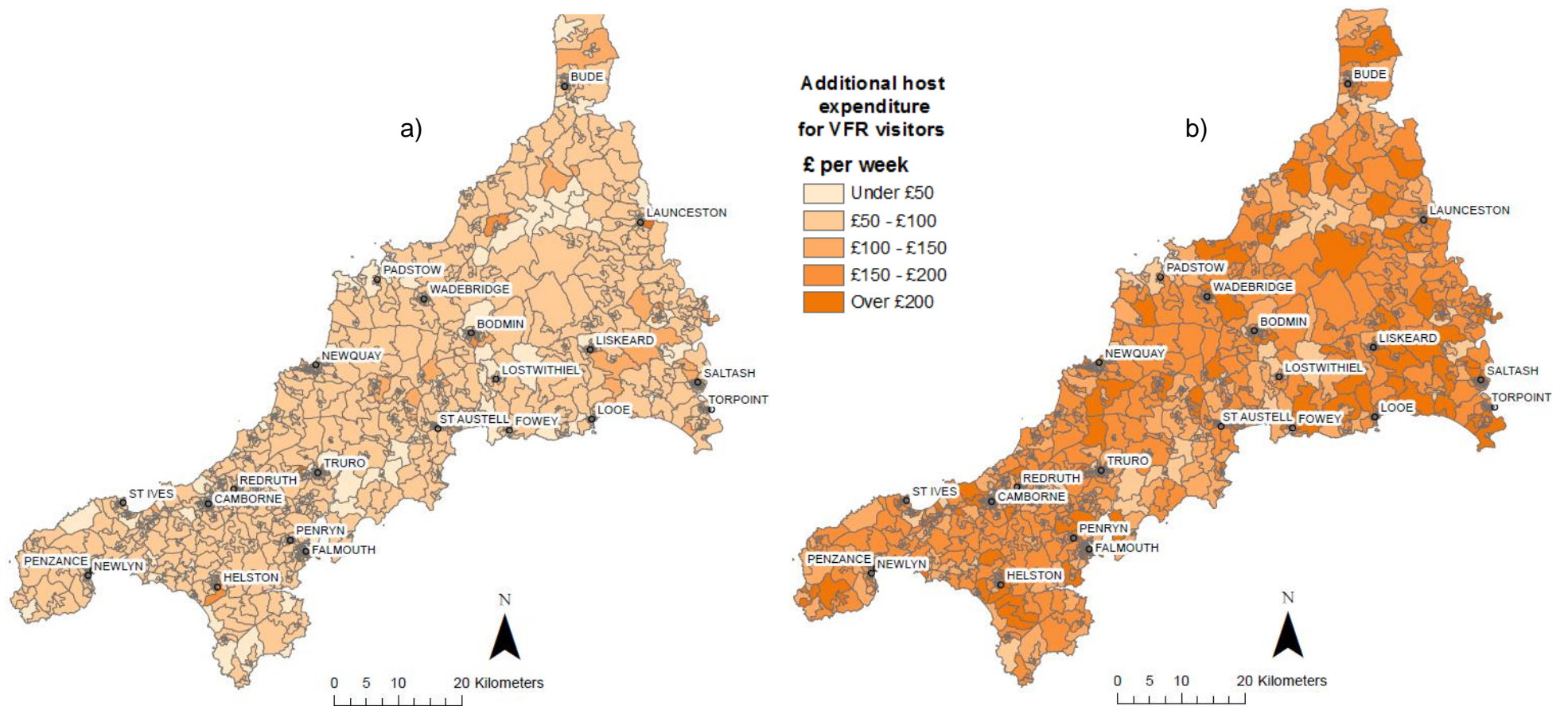
Figure 5.11 - Spatial and temporal pattern of host expenditure associated with VFR visitors

Incorporates host spending associated with day and overnight visitors during a) January and b) August.

correspond directly with the target year for the modelling being carried out, it represents the closest match between available datasets and reflects the fact that day visitors have traditionally been an under-researched area. Based on GBDVS (2011) data presented for the coastal destinations, 19% of these visits are thought to represent VFR, equating to almost 4.5m visits (VisitEngland, 2012). The host expenditure associated with these visits has been incorporated in the estimation of VFR spend in section 5.4.2.

21% of visits are reported to represent 'general days out' (including visits to the beach) (VisitEngland, 2012). It is these visits which are thought to generate some grocery expenditure, where purchases of snack-foods and top-up shopping (to take home) may take place in grocery stores. This is particularly likely to be true of stores such as the Newquay and Bude Sainsbury's, located centrally within these popular resorts and likely to experience demand uplift from these forms of day visitors. Although individual expenditure by these visitors may be insignificant, the volume of visitors, and the seasonal distribution (Figure 5.12) may drive considerable demand uplift at certain times of year. The remaining visits actually represent a leisure trip so long as these activities have a duration of over three hours and take place in a destination other than the participant's place of residence. These include visits where the primary purpose is to take part in sports, go out for a meal, visit the theatre or attend a special event of a personal nature (e.g. graduation). These activities are unlikely to drive any significant grocery expenditure within the destination and have been discounted from the demand estimation process.

As such, the GBDVS suggests that, across Cornwall as a whole, almost 5m day visits in 2011 were to major resorts and their beaches and attractions, which are likely to generate some destination-level grocery spend. The GBDVS suggests that visitors to coastal resorts spend an average of £44 per visit, with 17% of this expenditure (£7.48) being on food and drink purchased from shops or take-aways for immediate consumption (VisitEngland, 2012). In the absence of any further breakdown, it has been assumed that half this expenditure (£3.74 per visit) may be attracted to grocery stores.

Visitor numbers (and their associated expenditure) need to be distributed both spatially and temporally for inclusion in the demand layers. The seasonal distribution data used here is derived from the 2011 GBDVS, and has been extracted by the author as a cross-tabulation using their online data browser. The proportion of day visits to 'seaside resorts or towns' in the South West region by month has been extracted, as shown in Figure 5.12. Trips have been further disaggregated by week for compatibility with the existing residential and visitor demand estimates.

Visitor demand also requires spatial disaggregation so that the available day visitor spend is attached to individual OAs representing the major resorts within Cornwall. A total of 16 major resorts and towns are used (see Table 5.5). These resorts are likely to attract many of these day visitors and the Cornwall Visitor Survey (VisitCornwall, 2009) has been used to

distribute the day visitors spatially across the demand area, based on reported propensities for visitors to visit each resort or destination, shown in Table 5.5
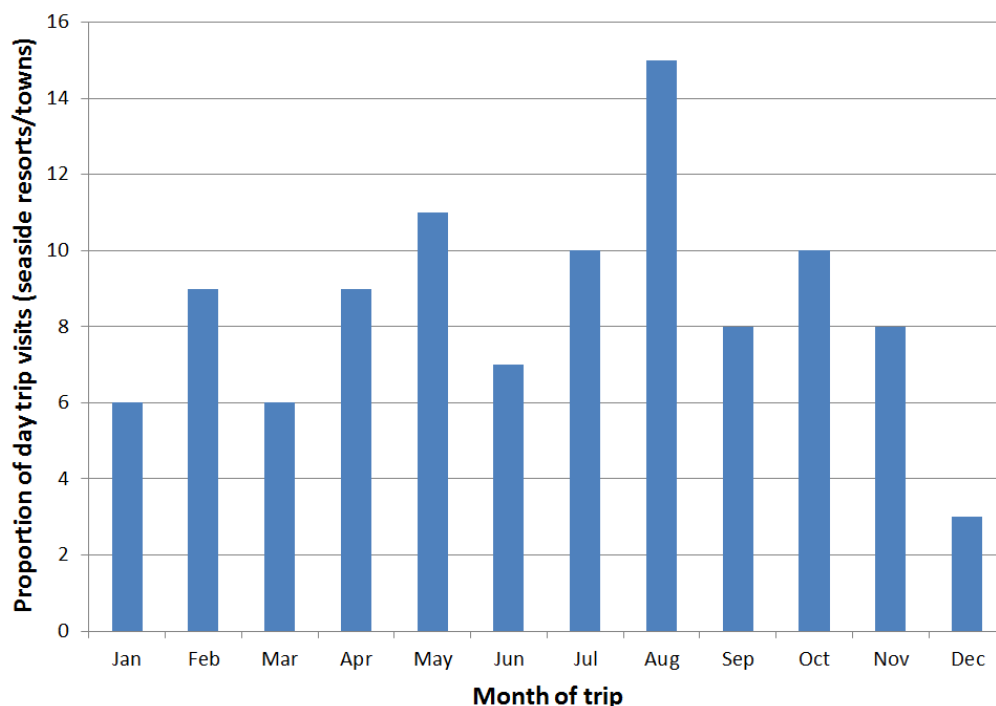
Figure 5.12 - Seasonal distribution of day trip visits to coastal destinations in South West England.

Derived from GBDVS 2011[22]

Table 5.5 suggests that destinations such as Newquay, Looe, Falmouth and St Ives experience considerable food and drink expenditure derived from day visitors to these resorts and their associated attractions or beaches (where applicable). Although very little information exists on actual small-area visitor numbers and their associated expenditure, this section demonstrates that the use of headline figures from national surveys such as the GBDVS, used in conjunction with localised rates and distributions, can be used to generate small-area estimates of their associated expenditure. It is acknowledge that the approach used is necessarily crude and is a consequence of a lack of suitable data collection or reporting at the local level.

Section 5.6 outlines seasonal and spatial patterns of demand in Cornwall, and expands on the issue of data availability.

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[22] http://dservuk.tns-global.com/gbdayvisitsLightEngland/

Table 5.5 - Spatial distribution of day visitor expenditure (August) to 16 major resorts and destinations.

Proportion of day visitors by resort derived from Cornwall Visitor Survey (VisitCornwall, 2009)

	Proportion of day visits	*Number of day visits (per week)*	*Day visitor expenditure (£ per week) August*
Bude	0.08	18,511	69,232
Falmouth	0.11	25,358	94,838
Bodmin	0.03	6,339	23,710
Boscastle	0.03	7,924	29,637
Fowey	0.03	7,132	26,673
Launceston	0.01	1,585	5,927
Looe	0.08	19,018	71,129
Newquay	0.11	23,139	86,540
Padstow	0.07	15,849	59,274
Penzance	0.06	13,471	50,383
Perranporth	0.04	8,717	32,601
St Ives	0.13	30,112	112,621
Tintagel	0.03	7,924	29,637
Truro	0.11	25,453	95,194
Mevagissey	0.03	7,924	29,637
St Austell	0.05	11,570	43,270
Total	**1**	**230,028**	**860,304**

5.6 Spatial and temporal grocery expenditure estimates

Using the approach outlined in sections 5.3 - 5.5, OA level grocery demand originating from visitors has been estimated, drawing on a range of local, regional and national data sources and surveys. Visitor demand has been calculated as:

$$V_i^{kt} = e^{kt} n_i^{kt} + h_i^t + d_i^t \qquad (5.2)$$

Where:

V_i^{kt} is a measure of the total available expenditure available in zone i by visitors using accommodation of type k during seasonal time period t.

e^{kt} is a measure of the average weekly groceries expenditure for visitors using accommodation of type k during time period t, drawn from a variety of survey sources.

n_i^{kt} reflects the number of visitors using accommodation of type k in zone i during seasonal time period t.

h_i^t represents spending by those hosting visitors in zone i during seasonal time period t.

d_i^t accounts for spending by day visitors in zone i during seasonal time period t.

The resultant demand layers thus incorporate all forms of overnight visitor, leisure day visitors and induced visitor spend by hosts. The seasonal and spatial patterns of visitor demand at the OA level are shown in Figure 5.13. Figure 5.13 shows 52 week average, along with weekly average expenditure on an OA-by-OA basis during the winter (December – February), spring (March – May), summer (June – August) and autumn (September – November). Peak-season demand (August) is also shown separately, representing the school summer holiday.

It is very clear from Figure 5.13 that the spatial pattern of visitor demand remains consistent across the year, with the overall magnitude increasing during the spring, peaking in the summer (and specifically August), and declining during Autumn and Winter. At all times, visitor demand is clearly spatially concentrated towards coastal resorts, with the clearest cluster representing a band running along the north coast, between St Ives and Bude (incorporating the resorts of Newquay and Padstow), with a similar pattern on the south coast between Falmouth and Looe, incorporating resorts such as Fowey.

During the peak-season, 7 OAs are estimated to generate over £100,000 per week additional visitor grocery spend. These spatial clusters of demand are driven by the presence of a very large holiday park or touring site in each OA. The same OAs generate a combined residential expenditure of just over £1,000 per week, representing just 0.1% of the total available expenditure in those demand zones at this time of year. Clearly therefore, small-area visitor demand can far outweigh residential demand in some areas at certain times of the year. Based solely on visitor demand, these estimates suggest that a total of over £7.3m additional grocery expenditure is available county-wide on an average week in August. Total residential demand for the corresponding period is just over £15.7m. Visitor demand therefore represents almost a 50% increase in demand during the peak-season. Total visitor expenditure falls to just under £500,000 per week in January, driven largely by lower occupancy rates and site closures across much of the self-catering accommodation stock.
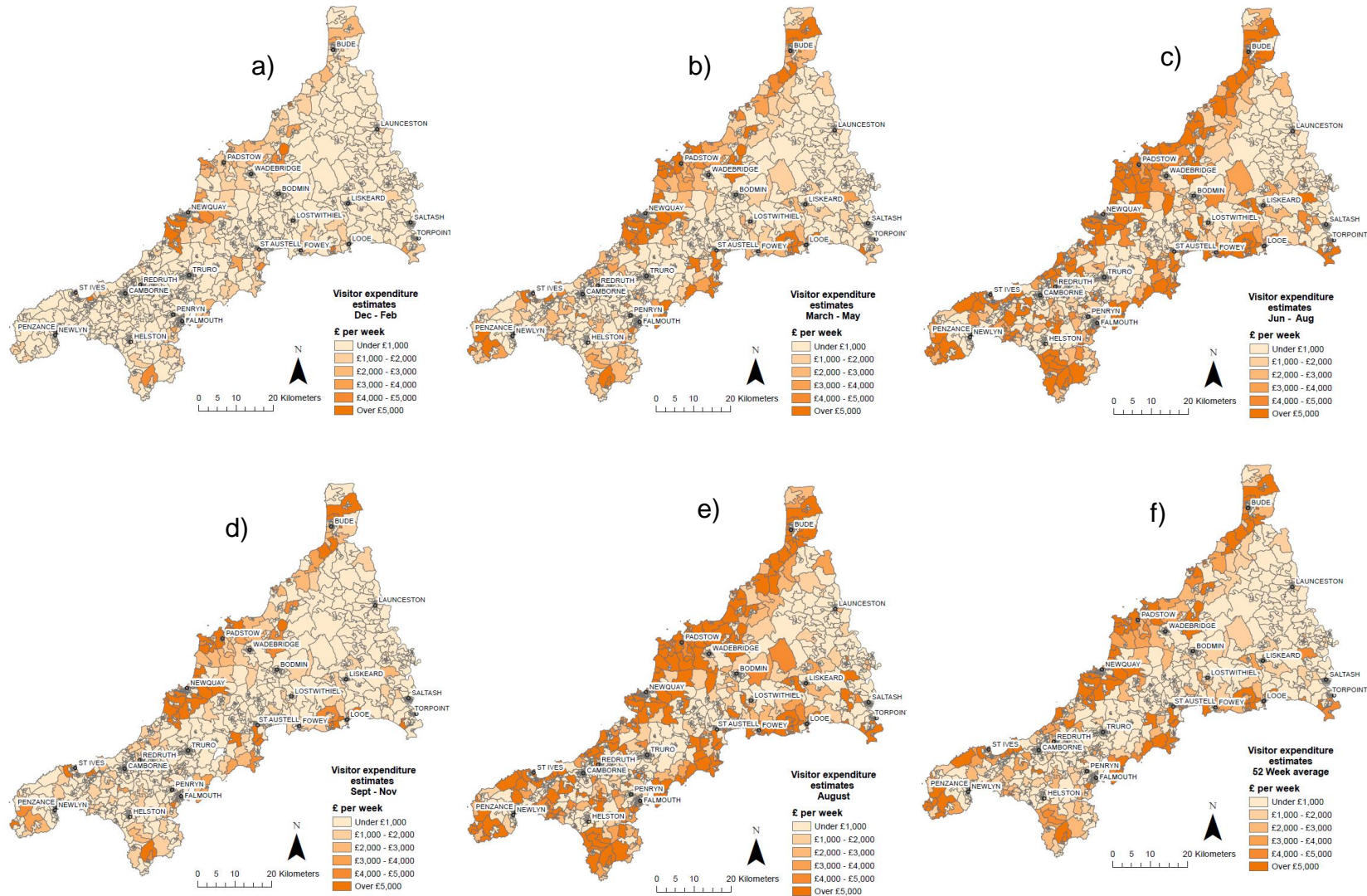
Figure 5.13 - Seasonal visitor demand estimates (average weekly spend) at the OA level

a) Winter (Dec-Feb, b) Spring (March – May) c) Summer (June – Aug) d) Autumn (Sept - Nov), e) August (peak school summer holidays) and f) 52 week Average

Table 5.6 identifies the proportion of total grocery demand attributable to local residents and to visitors (by type) during January and August. It is clear that the relative importance of residential demand is far greater in January, during which all forms of visitor demand contribute less than 3% of available expenditure. Visitor demand (including induced demand) represents over 30% of available expenditure in August (across the whole study area), with expenditure associated with visitors using commercial self-catered accommodation representing almost a fifth of the total grocery demand. Table 5.6 also suggests that the contribution of induced visitor demand (via VFR hosts and accommodation operators) is minimal in relation to other forms of visitor spend, representing around 3% of total grocery expenditure in August and less than 1.5% in January.

The demand estimates shown in Figure 5.13 clearly highlight that visitor expenditure exhibits a spatial and seasonal pattern that is distinct from residential demand (Figure 5.3). Visitor demand exhibits a far greater tendency to cluster spatially, and the overall magnitude of demand can be far higher, especially during peak periods. Any approach that attempts to estimate visitor demand by simply up-scaling residential demand is therefore considered misleading, since it fails to account for the spatial and seasonal characteristics of visitor expenditure.

Table 5.6 - Proportion of total available expenditure by origin – comparison of January and August

	January %	*August %*
Local Residents	95.3	68.3
Overnight visitors using commercial self-catered accommodation	1.2	17.3
Second home owners	0.9	5.2
VFR Hosts	0.9	1.7
Accommodation operators	0.5	1.4
Day visitors	1.7	6.1

In spite of the obvious benefits of this form of spatial and seasonal demand estimates, there remain a number of challenges in terms of developing, maintaining and validating the demand layers, which have been identified throughout the Chapter. In particular, validation is almost impossible since there is no reliable indicator of overall visitor numbers, their seasonal and spatial distribution or their associated grocery expenditure at the sub-regional level. Validation is thus wholly dependent on these estimates being used in a predictive capacity (Chapters 6 and 7), and their success will be evaluated based on their ability to replicate observed supply side characteristics (seasonal store revenue estimations). The

seasonal visitor demand estimates will be considered successful if, when used in conjunction with residential demand, they can replicate the observed supply side indicators in a modelling framework as carried out in the following Chapters.

5.7   Conclusions

This chapter sought to develop an approach to estimate small-area seasonal and spatial grocery demand for the county of Cornwall. The OA level estimates form an important input to the spatial modelling employed in Chapters 6 and 7 and are an important tool for store location planning in tourist areas. Where possible, a bottom-up approach has been used, enabling expenditure associated with all forms of visitor using commercial accommodation to be incorporated. Additionally, a top-down approach has been used to spatially and temporally disaggregate county-wide estimates of VFR host spend and spend associated with day visitors.

The approach used here seeks to incorporate all forms of direct and induced visitor grocery spend. A series of specific visitor demand layers have been created for use in location-based modelling, allowing visitor demand to be handled separately from residential demand within the spatial modelling, offering advantages in model calibration and parameter estimation (explored in Chapter 6). The monthly temporal scale of accommodation occupancy rates and headline visitor surveys allowed 12 seasonal layers to be produced, each reported in terms of weekly spend. 52 week average spend has also been calculated. Residential household demand, including seasonal expenditure outflow, has also been estimated on a monthly basis. The combination of both residential and visitor demand generates complete demand side estimates which can be used within store location planning and scenario evaluation to consider overall impacts on the supply side (see Chapters 6 and 7).

Developing the small-area expenditure estimates has represented a complex and time consuming task. Whilst a series of well-developed national surveys provide comprehensive insight into visitor characteristics and associated expenditure at a national or regional level, there remains a considerable weakness in data availability and insight at the small-area or sub-sector specific level. As such, very limited information is available on small-area visitor numbers or their associated expenditure on categories such as grocery.

A number of assumptions, backed up where possible by academic and industry sources, have had to be made. It is acknowledged that some may be crude or lack the robustness usually associated with demand estimation, yet they represent the best available. Furthermore, it is recognised that these demand estimates represent only a snapshot, based on data from 2010 and 2011, designed to coincide with the supply side data (2010), make use of occupancy data (not available beyond 2010), incorporate latest population counts from the 2011 census and tap into available research on day visitors (available from 2011 only).

The expenditure estimates could be estimated for any time period but would require sufficient input data. Occupancy/utilisation and expenditure rates can be altered easily to identify the impact of demand side changes, but this approach would assume that the accommodation stock itself remained static. In reality, the accommodation stock changes frequently and maintaining any form of comprehensive database of accommodation is almost impossible without the support of local tourist organisations.

Whilst this chapter has specifically sought to estimate small-area expenditure, the underlying small-area seasonal distribution of visitors, driven by their accommodation, is itself a previously un-researched and un-reported area. Chapter 3 situated this thesis within a broader context of understanding small-area non-residential populations, and the underlying seasonal and spatial distribution of visitors outlined within this chapter goes some way to address this need. Whilst not an objective of this study, Chapter 9 identifies a range of additional outputs that could be directly derived from the OA level seasonal 'visitor population' estimates that have been produced as part of the expenditure estimation process. For example, knowledge of the location and likely numbers of overnight visitors assists greatly with the provision of health services which, in areas such as Cornwall, face considerable strain from seasonal population influxes.

With the intended end users being retail location planning teams, it is recognised that all but the very best resourced teams will lack the manpower required to produce and maintain visitor demand estimates of this nature. Nonetheless the development and evaluation of modelling approaches (Chapters 6 and 7) demonstrates the considerable utility that these forms of expenditure estimation can bring to store-location planning. Given its important contribution to overall demand during the peak season, it is recommended that demand estimation should seek to incorporate visitor demand associated with self-catered accommodation and second home ownership.

With tourism representing an important driver of demand in the grocery retail sector, accurate estimations of small-area demand are needed. Chapter 8 develops similar estimates for additional study areas in Kent, and demonstrates that where suitable local data collection exists, the process does not necessarily have to be onerous and can generate robust store-level revenue estimates. Chapter 9 also reflects fully on the ability of location planning teams to generate and maintain demand side estimates of this nature.

It is acknowledged that there remain challenges in obtaining and preparing the data required to generate such estimates. Nonetheless, the expenditure estimates reported here provide a clear indication of the small-area seasonal and spatial patterns of grocery demand. This chapter has identified and integrated suitable data sources, outlining a clear methodology through which visitor expenditure can be estimated at the small-area level from a demand side perspective. Spatial and temporal variations are clearly evident in the demand layers produced, supporting the observations based on store-level data outlined in Chapter 4, and

confirming that visitor demand must be handled in a robust manner within location-based modelling.

Chapter 6 develops these layers further as an input to a SIM and demonstrates that they can produce improved store-level revenue estimates. The utility of the SIM is demonstrated fully in Chapter 7 which explores a number of supply side scenarios in Cornwall. Subsequently, Chapter 8 seeks to produce similar demand layers for selected districts in Kent, and identifies that the approach can be used successfully in destinations where the nature of visitor demand and magnitude of uplift is different.

Chapter 6: Developing and calibrating a disaggregate SIM of consumer grocery demand and supply

6.1 Introduction

Chapter 2 outlined the role of location analysis in retail planning and identified the important role that spatial interaction modelling has played within the location planning sector as a tool for estimating proposed store revenue. To recap, a spatial interaction model (SIM), applied to the retail sector, attempts to model consumer expenditure flows from demand zones to competing stores, taking account of the characteristics of demand and supply and representing a trade-off between the attraction of stores that provide increased 'opportunities' and the constraint of distance/travel 'cost' (Fotheringham and O'Kelly, 1989).

Chapter 5 developed small-area demand layers and outlined the available food and drink expenditure at an OA level. These considered both local residential demand alongside a series of seasonal demand layers which represent the seasonal sales uplift driven by tourism and experienced at certain times of year. The seasonal demand layers can be used in conjunction with small-area residential demand to account for the seasonal influx of visitors, alongside variations in the number of residents from within the area holidaying away from home. Visitor inflow incorporates visitors using all forms of overnight visitor accommodation, including those staying with friends and relatives, the subsequent induced grocery demand resulting from hosts and expenditure by day visitors to local resorts.

The case was made in Chapter 5 that this seasonal demand layer in itself represents a major advance in location planning. Understanding more about the small-area seasonal and spatial distribution of all forms of visitors and their associated expenditure is a crucial enhancement in a retailers' capacity to incorporate small-area seasonal demand in location-based decision making. Considered in conjunction with Chapter 4, retailers also benefit from an enhanced understanding of the linkage between in-store sales fluctuations and underlying drivers of visitor demand. This chapter seeks to demonstrate that the seasonal demand layers can be used to generate accurate and enhanced predictions of store-level revenue, especially compared to the existing crude and simplistic up-scale approach outlined in Chapter 2. First the classic production-constrained SIM is used in its most basic aggregate form to demonstrate that the seasonal demand estimates developed in Chapter 5 can generate enhanced predictions of store-level revenue.

Second, this chapter seeks to further develop the predictive capacity of retailers in tourist areas, developing the SIM further to improve its ability to replicate known consumer flows and predict store revenue or turnover with greater accuracy. This is achieved via model disaggregation on both the demand and supply sides, such that independent model

parameters can be set for different types of consumer and the relative attractiveness of different supply points can be controlled in relation to each demand type. The case for disaggregation is explored fully with reference to the literature and the nature of visitor and residential demand, acknowledging that different consumer types exhibit different behaviours and interact with retailers in complex and individualised ways.

The wealth of commercial consumer data available for this thesis offers an unprecedented opportunity to develop such a model and to validate and calibrate model flows using high quality and timely empirical data from Sainsbury's, thus addressing a clear gap in the literature. It should be noted that although the focus of this thesis is on estimating and incorporating seasonal visitor demand uplift within location planning, in order to fully integrate visitor demand within location-based modelling, evaluate the impact on store-level revenue estimation and run a number of 'what if?' scenarios (Chapter 7), it is also necessary to incorporate residential demand (as modelled at the small-area level in Chapter 5) within the spatial modelling framework.

This chapter is structured as follows. Section 6.2 takes the demand surfaces produced in Chapter 5 and uses a basic SIM to estimate store-level revenue. The use of this model demonstrates that the demand estimates, used in conjunction with industry standard modelling tools, are able to considerably improve the estimation of seasonal store revenue fluctuations driven by tourism. Sections 6.3 and 6.4 then seek to develop this predictive capacity further, outlining the disaggregate SIM developed for this application, with the model calibration and validation carried out in section 6.5. Sections 6.6 and 6.7 consider the model's ability to improve revenue predictions and potential implications for store location planning, which are explored in more detail in Chapter 9.

6.2 Classic production-constrained entropy maximising SIM for retail applications

As outlined in Chapter 2 the production-constrained entropy maximising SIM is commonly used in grocery retail applications. In its most basic form, the SIM is built up of three components relating to supply, demand and interaction (equation 6.1). Inherent in the application of the model is the concept that the expenditure available (O) within any given small-area (i) is shared by competing retailers (j) based on their relative 'attractiveness' (W_j) and accessibility. Their accessibility is a function of the relative 'cost' in terms of distance (C_{ij}), calibrated using a distance decay parameter (β) which reflects the willingness or ability of consumers to travel to interact with supply.

$$S_{ij} = A_i O_i W_j \, exp^{(-\beta C_{ij})} \qquad (6.1)$$

Where: S_{ij} represents the interaction or expenditure flow between demand zone i and store j

A_i is a balancing factor which takes account of competition and ensures that all demand is allocated to stores within the region. It is calculated as:

$$A_i = \frac{1}{\sum_j W_j \ exp^{-\beta C_{ij}}} \qquad (6.2)$$

O_i represents the expenditure available in residential zone $_i$

W_j accounts for the attractiveness of store $_j$

$exp^{-\beta C_{ij}}$ is the distance deterrence term, incorporating β, the distance decay parameter, and C_{ij}, the distance or travel time between zone $_i$ and store $_j$.

(Source: Adapted from Birkin and Clarke, 1991; Birkin *et al.*, 2002; Wilson, 1971; Wilson, 2010)

The model used here, based on equation 6.1, and implemented by the author, operates as a series of Microsoft Excel spreadsheets and macros. This section does not dwell on the specific characteristics of the model: these are considered fully, with reference to the literature and established industry best practice in sections 6.3 - 6.5. The use here of this basic form of the SIM is instead intended to demonstrate, albeit rather crudely, that the visitor expenditure estimates developed in Chapter 5 are able to generate robust and considerably improved revenue predictions at the store-level, which is the overall objective of this thesis. Having established that the SIM, used in conjunction with visitor demand estimates, can generate revenue predictions of the right order of magnitude, the Chapter then seeks to develop the SIM further (section 6.3) via disaggregation, in order to improve its ability to generate robust revenue predictions and thus further the capacity of location planning teams to employ spatial modelling to estimate store revenue in tourist areas. It is in the context of the disaggregated model (section 6.3 onwards) where the characteristics of the model, the input data and the calibration and validation are discussed fully.

During this application of the model, which is in its most basic form, store size is used as a proxy for store attractiveness. The model allocates expenditure to 103 separate stores that fall within the study area (Cornwall) or within neighbouring West Devon and within a reasonable travel time of residents living towards the east of the county. These stores include all supermarkets and foodstores over 10,000 square foot, plus selected Tesco express and Co-Op stores of below 10,000 square foot in centres where the addition of this store provides an important element of consumer choice (e.g. Liskeard) or represents a high proportion of the available floorspace (e.g. Par). Smaller convenience stores such as those operated by Spar, Nisa and Londis have not been incorporated since these tend to serve only their immediate neighbourhood, offering a very limited range of top-up food and drink.

As highlighted in Chapter 2, the use of floorspace is common and assumes that consumers demonstrate a willingness to travel further to access larger stores. The use of store size and alternative representations of the supply side attractiveness are considered further in section 6.4.2. The distance deterrence term has been computed using recorded road travel

times, taking account of the nature of store catchments in Cornwall and recognising the likely importance of the road transport network in determining store choice, outlined fully in section 6.4.3.

On a store-by-store basis, the model is able to estimate the inflow of consumer expenditure, modelled as the available food and drink spend, originating from both residential and visitor demand, in £ per week. The total inflow to any given store represents the weekly food and drink revenue for that store. Modelled flows (residential demand) were calibrated against known consumer flows (for four Sainsbury's stores) from Sainsbury's Nectar loyalty card data, calibrated via an iterative procedure whereby the distance decay (β) parameter, incremented through a series of values, with the average trip distance (ATD) and a range of goodness-of-fit (GOF) statistics calculated and recorded for each iteration. The aim of this routine was to minimise the difference between observed and predicted ATD and to demonstrate, via selected GOF statistics (R^2, SRMSE), that the modelled flows were able to replicate observed flows to an acceptable level of accuracy. Section 6.5 details the calibration routine and GOF statistics chosen, with reference to the disaggregated model.

6.2.1   Revenue prediction using the aggregate SIM

Recall that the use of a SIM here is to demonstrate the potential utility of a SIM in handling visitor demand – producing revenue estimations that are more accurate than traditional approaches, and proving sufficient flexibility to model characteristics of seasonal visitor demand. Following calibration, it is possible to compare the estimated store revenue using the SIM with the actual revenue recorded in the four Sainsbury's study stores of interest (see Chapter 4). Table 6.1 shows the ratio of observed (store trading data) to predicted (modelled) revenue for the four stores of interest, for each seasonal time period (Jan – December 2010, plus 52 week average for the 2010 trading year). A value of 1.0 signifies that the observed and predicted revenue correspond, whereas greater than 1.0 demonstrates that the model has over-predicted store revenue and vice-versa. The observed store revenue (food and drink spend) is derived from Sainsbury's store trading information and has been averaged from weekly sales figures on a month-by-month basis, (but is not shown in its raw form in order to preserve confidentiality of store trading information).

Table 6.1 demonstrates that, when used in conjunction with visitor demand estimates, the aggregate SIM can achieve some form of accuracy in terms of store revenue predictions at the four study stores. Considering first the 52 week average store sales, model predictions are within 5% at three stores, but underestimated at Newquay by around 15%. This is reflected in the monthly revenue estimations, where Newquay is consistently underestimated (with the exception of May), especially during the summer months, suggesting that this store, which is located in the centre of a major tourist resort, is popular among consumers.

The store in the popular coastal resort of Bude is also underestimated in the high season, but, in contrast to Newquay, overestimated in the low/fringe season. The degree of variability is

also greatest here, with the ratio of observed to predicted ranging from 0.77 to 1.33. The underestimation in August is undoubtedly driven by visitor demand, with visitors staying elsewhere in Cornwall and West Devon likely to visit this popular resort, which is within easy access of the A39 primary route. The considerable overestimation in February is more likely to result from inaccuracies within the occupancy rate data used to estimate visitor numbers. In February, which is part of the low season, many accommodation units may only have been operating for half term school holidays, yet reported their occupancy for that week as if it represented their average occupancy across the whole month.

Table 6.1- Ratio of observed to predicted store revenue (predicted/observed) for four Cornish stores using the aggregate SIM

2010 Data	Newquay	Bude	Bodmin	Truro	Average
52 WK Ave	0.85	1.03	0.97	0.96	**0.95**
Jan	0.91	1.2	0.98	1.02	**1.03**
Feb	0.97	1.33	1.0	1.01	**1.08**
Mar	0.86	1.14	0.9	0.96	**0.97**
Apr	0.95	1.15	1.08	1.0	**1.05**
May	1.01	1.21	1.06	1.02	**1.08**
Jun	0.84	0.95	1.01	1.03	**0.96**
Jul	0.8	0.95	1.01	1.05	**0.95**
Aug	0.83	0.77	1.02	1.04	**0.92**
Sep	0.87	1.07	0.95	0.9	**0.95**
Oct	0.82	1.01	0.98	0.94	**0.94**
Nov	0.79	1.19	0.86	0.82	**0.92**
Dec	0.78	1.01	0.76	0.72	**0.82**
Max	**1.01**	**1.33**	**1.08**	**1.05**	**1.08**
Min	**0.79**	**0.77**	**0.86**	**0.82**	**0.92**
Range	**0.22**	**0.56**	**0.22**	**0.23**	**0.16**

Note: **Max**, **Min** and **Range** exclude December (Christmas uplift)

$R^2 = 0.74$ SRMSE = 0.06

The non-resort based Bodmin and larger Truro stores exhibit revenue predictions that are consistently within 10% of recorded store revenue, except during November and December. These stores have their greatest degree of underestimation in December. This is not

unexpected since December is a recognised period of sales uplift for all food retailers, which is largely driven by higher than average spend on a transaction-by-transaction basis, rather than by additional non-residential demand. Retailers are able to forecast this form of demand uplift using different approaches, so the apparent underestimation at this time of year is not a concern in this context. The degree of variability and the general magnitude and pattern of over and under estimation at the Bodmin and Truro stores is very similar, suggesting that the model is working well.

Table 6.2 compares the modelled revenue using the visitor demand layer with the results obtained using the same model using just the residential demand layer with a 30% demand uplift. As noted fully in Chapter 2, demand uplift factors of this magnitude are commonly applied to assess retail demand within planning applications. Within Chapter 5, it was argued that this crude approach was completely unable to account for the seasonal and spatial differences between residential and visitor demand. Table 6.2 clearly supports this assertion and demonstrates that, whilst 52 week average revenue predictions are reasonable using an up-scaling approach, clear overestimation in January, and subsequent underestimation in August (by up to 50%) highlights that this approach cannot take account of seasonal and spatial variations in demand at different points within the tourist season.

Table 6.2- Modelled predicted/observed revenue using up-scale approach and visitor demand layers

Pred/Obs	Newquay	Bude	Bodmin	Truro	Average
52 week Average					
Upscale	0.88	0.89	1.08	1.08	**1.03**
Demand Layer	0.85	1.03	0.97	0.96	**0.95**
January					
Upscale	1.24	1.37	1.25	1.22	**1.24**
Demand Layer	0.91	1.2	0.98	1.02	**1.03**
May					
Upscale	0.93	0.96	1.08	1.06	1.03
Demand Layer	1.01	1.21	1.06	1.02	**1.08**
August					
Upscale	0.56	0.50	0.96	1.00	**0.83**
Demand Layer	0.83	0.77	1.02	1.04	**0.92**

The model's ability to predict revenue reasonably accurately when used in conjunction with the SIM is very encouraging, especially given the simplicity of the model used, treating all consumers similarly and calibrating based on a single β parameter. Benoit and Clarke (1997) note that such a model is likely to over-generalise consumer behaviour, recognising that the use of a single parameter (in this case β) is unlikely to be able to effectively model behaviour by all types of consumers or be appropriate for all store types. As such, the use of a disaggregate model, where parameters can be set independently for different consumer or store types, may give greater flexibility to handle some of the nuances exhibited in seasonal demand, such as the increased attractiveness of certain stores (such as those in coastal resorts) to certain consumers at certain times of year, or particular brand preferences and loyalties exhibited by consumers. These ideas are explored throughout the remainder of this chapter.

6.3 Disaggregate production-constrained SIM

6.3.1 Examples within the literature

The literature suggests that, with appropriate calibration, the aggregate level production-constrained SIM can predict consumer flows to an acceptable level of accuracy and thus achieve robust revenue predictions (e.g. see Birkin *et al.*, 2002). As shown in section 6.2, the use of this production-constrained SIM has enabled revenue prediction to within 10% of reality at some of the study stores used. This is in-line with the current performance of Sainsbury's in-house spatial interaction model, which is able to predict revenue to within 10% of reality around 70% of the time (Wright, 2011). Nonetheless, the Sainsbury's board require all forecasts to be consistently within 5% of the actual trading patterns (Wright, 2011). Whilst the incorporation of visitor demand in a similar modelling framework has improved the accuracy of predictions (particularly in comparison to up-scaling on a monthly basis), there clearly remains scope to improve the predictive capacity of the SIM, especially to meet the accuracy levels expected by major retailers.

There are a number of obvious limitations inherent in the application of the aggregate level SIM, most notably its handling of all consumers as one homogeneous group that are thought to exhibit similar decision making behaviour. Whilst it is accepted and acknowledged that no SIM will ever be able to capture all possible consumer behaviours, there is scope to improve the ability of the SIM in order to capture greater consumer decision making behaviour in terms of how and where they interact with supply. It is realistic to assume that, based on factors such as age, geodemographic or socio-economic status and income, consumers will exhibit more individualised behaviours. In particular the literature suggests that certain groups of consumers may have a higher propensity to travel further to the store of choice, and that certain retail brands may be more attractive to certain types of consumer based on their income (e.g. see Fotheringham and Trew, 1993).

As such the aggregate level spatial interaction model often requires disaggregation on the demand or supply side in order to estimate flows based on more specific characteristics of demand, interaction or supply and thus to accurately handle the complex behaviour of different groups of consumers (Benoit and Clarke, 1997; Birkin *et al.*, 2010a; Birkin *et al.*, 2004; Wilson, 1971; Wilson, 2010). This section outlines how key parameters and constraints within a SIM can be disaggregated by consumer and store type, allowing the model to handle some of the more complex and individualised behaviour of different groups of consumers, and to take account of key socio-economic characteristics that drive expenditure and store choice.

It is recognised that the characteristics of demand and the attractiveness of supply will vary according to income, age, ethnicity or other socio-economic characteristics of the consumer, and may also vary depending on the type of product in question. Disaggregation may thus be as straightforward as applying different β values for different groups of consumers to account for the fact that a single β value is unlikely to be able to represent all the different complex consumer flows that exist. For example, in an application of a SIM to estimate the impacts of the new Silverburn regional shopping centre near Glasgow, Scotland, Khawaldah (2012) applied different β values for consumers in each postal area, recognising that those residents in geographically remote postal areas were less likely to be over-sensitive to the impact of distance due to the inevitable longer journeys involved in accessing key shopping centres.

There remains, however, a considerable gap in the literature which explores fully the development and calibration of disaggregated spatial interaction models for real-world commercial applications and, whilst it is acknowledged that many such applications have been carried out, these are simply not represented in the literature (Birkin *et al.*, 2010a; Wilson, 2010). As such, much of the discussion that follows is based on the experience of a group of geographic modellers based at the University of Leeds, and who, since the mid-1980s, have developed considerable knowledge and practical experience building such models for commercial application, many carried out through GMAP Ltd. Some of their experiences and insights are documented through review articles, of which Birkin *et al.* (2010a) and Birkin *et al.* (2010b) provide an excellent overview from an applied modelling perspective. Birkin *et al.* (2010a) is drawn upon heavily here because these authors probably have more experience than anyone in developing and calibrating SIM that actually work for business applications.

Birkin *et al.* (2010a) suggest that retail brand is increasingly important in determining consumer flows. One particular study of stores in Leeds, West Yorkshire, recognised that, at the time, Sainsbury's and Tesco were considered more attractive than other grocery retailers, and, assuming all other things being equal, a square foot of a Sainsbury's or Tesco was relatively more attractive to consumers than a square foot of a competing retailer (Benoit and Clarke, 1997). They also suggested that β should vary to reflect the mobility of individual

consumers, and to reflect consumer willingness to travel further to reach certain brands. Benoit and Clarke therefore made use of a SIM disaggregated by consumer type (k) and store brand (n). The SIM is shown in equation 6.3. The relative attractiveness of different stores was controlled using two variables, W_j representing the overall attractiveness of store j, measured using traditional store floorspace, and θ_j^n, the additional attractiveness of store j, measured via brand market share. The demand side was also disaggregated, handling different consumer types within the demand estimation through the term O_i^k, representing the purchasing power of different consumers based on their geodemographic or socio-economic characteristics.

$$s_{ij}^{kn} = A_i^{kn} O_i^k \theta_j^n \, W_j \, exp^{(-\beta_i^k c_{ij})} \qquad (6.3)$$

Where: s_{ij}^{kn} represents the expenditure flow between zone $_i$ and retail destination $_j$, by consumer of type k for store brand n.

A_i^{kn} is a competition factor which ensures that all demand is allocated to stores in the region. It is calculated as:

$$A_i^{kn} = \frac{1}{\sum_j W_j \, \theta_j^n \, exp^{(-\beta_i^k c_{ij})}} \qquad (6.4)$$

O_i^k is the demand or expenditure available in residential zone i by consumer of type k.

W_j accounts for the attractiveness of centre/store j

θ_j^n is the additional attractiveness of retailer n at centre j

$exp^{(-\beta_i^k c_{ij})}$ is the distance term and includes the travel time C between zone i and centre j, and the distance deterrence parameter β, which reflects the willingness or ability of consumer of type k in zone i to travel in order to purchase goods.

Source: Adapted from Benoit and Clarke (1997)

Benoit and Clarke (1997) demonstrate, with reference to ASDA store turnover in West Yorkshire, that the use of a disaggregate SIM of the form shown in equation 6.3 can produce revenue predictions that are considerably more accurate than 'off-the-shelf' aggregate level models. Their study remains one of the only examples in the literature where model predictions have been calibrated against empirical data from a major grocery retailer. Their use of empirical data provides clear evidence that disaggregation by both consumer type (k) and store brand (n) afforded great potential to improve revenue predictions by capturing the additional attractiveness associated with certain brands, and the spending power of different consumer groups. The model applied in this thesis is based on the same principle as the grocery model used by Benoit and Clarke (1997), but seeks to develop further the link between consumer type and retailer type/brand, incorporating ideas about the relative

attractiveness of different retailers or brands to different consumer types, as explored in section 6.3.2.

6.3.2 Disaggregate SIM for this study

Chapter 4 noted that household level grocery demand is often habitualised, with consumers exhibiting brand loyalty through routine, habit, in-store promotions and perceptions of quality. Chapter 4 also identified that visitors are likely to display some form of brand loyalty when away from home, often motivated to shop with their existing retailer through familiarity or routine. As a result, certain consumer groups (e.g. those with the highest income) may view certain stores (such as those operated by M&S or Waitrose) as relatively more attractive than others, even where floorspace and distance may suggest otherwise in the model. Drawing on the disaggregate model used by Benoit and Clarke (1997), a disaggregated SIM should thus be developed in order to reflect:

> a) the relative attractiveness of different stores, brands or fascias to different groups of consumers; for example based on their affluence or age, and

> b) the ability or willingness of different consumer groups to travel further to access the store, brand or fascia of choice, which is also likely to be based on affluence, car ownership and other similar factors.

The disaggregate model used is shown in equation 6.5. Unlike Benoit and Clarke (1997), this model does not introduce θ in order to reflect additional brand attractiveness. Instead, a power function (α^{kn}) is incorporated within the attractiveness term in order to apply a measure of relative brand attractiveness to the existing attractiveness term on a consumer-by-consumer basis, as explored in section 6.4.2.

$$S_{ij}^{kn} = A_i^k \, O_i^k \, W_j^{\alpha^{kn}} \, exp^{(-\beta^k c_{ij})} \qquad (6.5)$$

Where: S_{ij}^{kn} represents the predicted expenditure flow between zone $_i$ and store $_j$ (of brand n) by consumer of type k.

A_i^k is a balancing factor which takes account of competition and ensures that all demand from zone $_i$ by consumer type k is allocated to stores within the modelled region. The balancing factor thus ensures that:

$$\textstyle\sum_j S_{ij}^{kn} = O_i^k \qquad (6.6)$$

It is calculated as:

$$A_i^k = \frac{1}{\sum_j W_j^{\alpha^{kn}} \, exp^{(-\beta^k c_{ij})}} \qquad (6.7)$$

O_i^k is a measure of the demand or expenditure available in demand zone i by consumer of type k.

W_j reflects the overall attractiveness of store j, whilst α^{kn} represents the additional or perceived relative attractiveness of store j for consumer type k and by store type (brand) n.

C_{ij} is the distance (although in this application, travel time is used) between zone i and store j, and incorporates the distance deterrence/decay parameter $exp^{-\beta^k}$ for consumers of type k.

(Source: Developed with reference to Birkin *et al.* (2010a); Clarke (2011))

The model takes the same form as the classic production-constrained SIM, yet the balancing factor (A_i) demand (O_i) supply (W_j) and distance deterrence ($exp^{-\beta C_{ij}}$) terms have been modified to incorporate different consumer types (k). An additional parameter, termed alpha (α), has also been incorporated on the supply side. α modifies the attractiveness term (W_j) to reflect the relative attractiveness of one store type, fascia or brand (n) over another, by consumer type. The inclusion of these terms allows both supply and demand to be disaggregated independently, yet the links between them maintained through the recurrence of consumer type (k) on both the demand and supply side.

The SIM has been developed separately by two parallel research projects in the School of Geography, University of Leeds. On-going work (see Thompson, 2013; Thompson *et al.*, 2012; Thompson *et al.*, 2010) aims to develop and validate a similar model to replicate flows of household grocery expenditure in West Yorkshire. In particular, Thompson's work makes use of Axciom consumer survey data to identify reported grocery consumption habits by household characteristics, a crucial step in understanding how different household types (as a proxy for consumer type) interact with grocery supply. His study has been used here to develop an understanding of the relative attractiveness of different brands to different types of consumer and informs the application of different β values for different household types.

The disaggregation by both consumer type and retailer type affords tremendous potential for the model to incorporate flows between different consumer types and different retailers, through modified attractiveness and distance terms. The attractiveness term ($W_j^{\alpha^{kn}}$), allows the relative attractiveness of different store types to vary by consumer type and can be visualised in the matrix shown in Figure 6.1. Figure 6.1 attempts to illustrate that the attractiveness of a particular store to a given consumer (household) is a product of both household and store characteristics, hence the need to disaggregate by both supply and demand. The conceptual illustration is based on the premise that discount retailers will be relatively more attractive to low income households and, with increased affluence, the attractiveness of discount retailers will fall, whilst the relative attractiveness of high end retailers (i.e. Sainsbury's, Waitrose and M&S) will increase.

n – Store/Retailer Type			Discount				Premium

Figure 6.1 - Relative store attractiveness by household type

Whilst Thompson is able to incorporate observed consumer behaviour into the assumptions that drive flows, the dataset he is using doesn't allow store-level revenue and inflow (on the supply side) to be validated against *recorded* store or consumer level data (and thus relies on *reported* shopping habits). This thesis plays a major part in the development of the model not only through the addition of visitor demand, previously omitted from all forms of spatial interaction modelling, but also by calibration and validation against store and consumer data supplied by Sainsbury's. This study also develops the model further via application to two study areas, Cornwall and then (in Chapter 8) for East Kent.

This thesis calibrates and validates the model against empirical store and loyalty card data from Sainsbury's. The use of genuine commercial data, and the notion that Sainsbury's are the intended end-user also addresses Birkin *et al*.'s (2010a) assertion that models produced for specific private sector applications are able to replicate consumer behaviours with some accuracy. This work forms a very important component in the development and validation of this form of model, particularly for use in investigations of expenditure flows for groceries. Section 6.4 considers the input demand and supply side data, including incorporation of visitor demand, before section 6.5 addresses model calibration and validation.

6.4 SIM development for modelling consumer demand and supply – an application in Cornwall.

6.4.1 Demand

Section 6.3 noted that the model is disaggregated by consumer type on both the demand and supply side. The demand side has been addressed extensively in Chapter 5, which outlined and justified, in some detail, the production of temporal small-area demand estimates. Recall that residential demand is segmented by household type (O_i^k). This allows the small-area

available residential expenditure to be built up from a household level based on geodemographic and socio-economic characteristics (and surveyed expenditure). As outlined in Chapter 5, the OAC is used in conjunction with OA level household counts from the 2011 census. Residential demand has been calculated for 12 monthly time periods, plus a 52 week average. It is based on household level demand and incorporates workplace inflow/outflow and the seasonal outflow of local residents holidaying elsewhere (see Chapter 5).

Demand has been calculated as:

$$O_i^{kt} = e^{kt}n_i^{kt} \qquad (6.8)$$

Where:

> O_i^{kt} is a measure of the total available expenditure available in zone i by consumer type k during seasonal time period t.

> e^{kt} is a measure of the average weekly groceries expenditure for consumer type k during time period t, taken from the living costs and food survey.

> n_i^{kt} reflects the number of consumers of type k in zone i during time period t.

Visitor demand is added as a separate series of layers again for 12 monthly periods and a 52 week average. These layers incorporate spending by visitors from all forms of overnight accommodation, including visitors using rented self-catering accommodation, camping and caravanning, staying in a second home or with friends and relatives. Additional spending by those hosting visitors, along with spending by day visitors is also included.

Visitor demand has been calculated as:

$$V_i^{kt} = e^{kt}n_i^{kt} \qquad (6.9)$$

Where:

> V_i^{kt} is a measure of the total available expenditure available in zone i by visitor of type k during seasonal time period t.

> e^{kt} is a measure of the average weekly groceries expenditure for visitor type k during time period t, drawn from a variety of survey sources and informed by loyalty card analysis.

> n_i^{kt} reflects the number of visitors of type k in zone i during time period t.

See Chapter 5 for a full discussion of how e^{kt} and n_i^{kt} have been calculated for both residential and visitor demand, including the data sources and rates used. Due to the way they have been calculated, residential and visitor demand are fed into the model separately – thus their parameters and their impact on flows and revenues can be clearly seen.

6.4.2 Supply

The attractiveness of a retail centre is often thought of in terms of retail floorspace, which in itself can be considered a proxy for a variety of other attributes that make a store relatively more attractive to a consumer – in many cases, for example, larger stores may be more likely to offer a greater range of products, benefit from more parking, longer opening hours or even lower prices (economies of scale) (Birkin *et al.*, 2002). Within the grocery sector, floorspace information is commonly collected by retailers who carefully monitor competitor networks. In this application, retail floorspace is used as the basis of the attractiveness term and has been derived from floorspace information held by GMAP consulting (now part of the CallCredit information group). The data was extracted for all stores in the study area from their Microvision software, using the most up-to-date data available in January 2013. The floorspace data was extensively verified and updated by the author using Sainsbury's own data (for both their own network and competitors), floorspace values reported in the Cornwall Retail Study (CRS) (GVA Grimley, 2010) and a variety of historic planning applications for store development and extensions within Cornwall[23].

Within their spatial interaction modelling tools at GMAP, Birkin *et al*. (2010a) note that they sometimes used a more complex representation of attractiveness, incorporating measures of centre and individual store attractiveness (parking, visibility, opening hours, number of floors), brand loyalty, store agglomeration and the maturity of individual retail outlets, alongside floorspace, often incorporated via a scorecard approach (Birkin *et al.*, 2010b). A body of influential work by Fotheringham has considered the issue of agglomeration in detail, suggesting that such models are unrealistic in assuming that consumers choose between all possible alternative stores. He suggests that instead, competing stores that are adjacent to each other may be viewed as one destination by consumers, resulting in a hierarchical choice; first selecting a possible destination and then stores within it (Fotheringham *et al.*, 2001). In that case, he would suggest that it is important to model flows to the destination first and subsequently to individual stores (see Birkin and Foulger, 1992 for an example applying this principle using WHSmith; or Birkin *et al.*, 2004 for a more generic discussion).

Whilst it is important to note that more complex representations of the supply side attractiveness do exist, for the purpose of this thesis store floorspace is used in conjunction with a measure of brand attractiveness. In particular, the wealth of experience built up by Birkin *et al*. (2010a) working with clients suggests that in the case of supermarkets, representing flows to individual stores (rather than to retail centres or other agglomerations) is realistic (indeed Fotheringham (1983) notes that the high degree of competition in the

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[23] Accessed via the UK planning portal - http://www.planningportal.gov.uk

grocery market means that distance, access and attractiveness are more important than agglomeration). The approach adopted here thus considers individual store attractiveness.

Birkin *et al.* (2010a) note that the ability of models to represent and discriminate between different brands is becoming increasingly important, since brand identities are an important tool thorough which to maintain market share. This is particularly true in the grocery sector, where purchasing is relatively routine and habitualised and retailers frequently use loyalty schemes and promotions to maintain customer patronage (see Chapter 2). For example, the Sainsbury's brand has a limited ability to perform well in low income areas, with consumers in these areas instead valuing the presence of ASDA and Morrisons alongside discount retailers such as ALDI and Lidl (Clarke *et al.*, 2012). Brand loyalty can be an important factor that is hard to capture through the use of floorspace alone. Within this model, brand loyalty is incorporated via the alpha (α) parameter, allowing store attractiveness to be disaggregated by retail brand (n). Alpha operates as a power function applied to individual store attractiveness values (floorspace) ($W_j^{\alpha^{kn}}$), thus making a unit of floorspace at store j of brand n relatively more or less attractive to consumers of type k. α has been set with reference to work carried out by Thompson *et al.* (2012) using Acxiom consumer survey data.

Thompson *et al.* (2012) use Acxiom's research opinion poll (2009 and 2010 data) in combination with the OAC classification to identify each retailers' customer base. They create a location quotient for each retailer, dividing that retailer's observed customer breakdown (by OAC group) by the underlying distribution of population across the OAC groups in their study region. As such, their location quotients identify whether a particular OAC group is over or under represented in a retailers' customer profile. They note, for example, that Waitrose, M&S and to some extent Sainsbury's all generate far higher than expected patronage from the affluent 'city living' supergroup, whilst the same is true of ASDA in the 'blue collar communities' supergroup, Co-Op in the 'countryside' supergroup and Sainsbury's in the 'prospering suburbs' supergroup.

The location quotients produced by Thompson *et al.* (2012) have been used here to inform the use of additional brand attractiveness, via the alpha parameter, for each retail fascia and each consumer group (for residents only). In Chapter 4 it was noted that the visitor trade at Cornish coastal stores exhibits a higher propensity to be from the slightly more affluent prospering suburbs supergroup, and as such the ability to vary store attractiveness by consumer socio-economic status is important. The location quotients have been rescaled around the value of 1, since alpha operates as a power function on the store attractiveness (floorspace) in the model. As such, store floorspace is raised to a power, depending on the individual combination of customer type and store brand/fascia, thus recognising that a unit of floorspace of Waitrose is more attractive than a unit of floorspace of ASDA to certain household types. The rescaled location quotients are shown in Table 6.3.

Table 6.3 - Brand location quotients for use in disaggregated SIM

Brand (Retailer)	OAC Supergroup						
	1	2	3	4	5	6	7
	Blue Collar	City Living	Countryside	Prospering Suburbs	Constrained by Circumstances	Typical Traits	Multicultural
Aldi	0.9980	0.9970	1.0051	0.9987	1.0025	1.0005	0.9952
ASDA	1.0076	0.9912	0.9904	0.9970	1.0023	0.9992	1.0013
Co-Op	1.0020	0.9990	1.0157	0.9922	1.0008	1.0000	0.9894
Lidl	1.0015	0.9995	1.0066	0.9962	0.9957	0.9997	1.0091
M&S	0.9891	1.0381	0.9967	1.0066	0.9952	1.0051	1.0003
Morrisons	1.0005	0.9942	0.9997	0.9987	1.0020	1.0005	0.9990
Sainsbury's	0.9904	1.0121	1.0013	1.0088	0.9942	1.0028	0.9997
Tesco	0.9992	0.9987	1.0071	1.0010	0.9965	0.9990	0.9985
Waitrose	0.9811	1.1000	1.0061	1.0124	0.9843	1.0023	1.0068
Iceland	0.9997	0.9982	1.0058	0.9975	0.9991	1.0001	1.0021

6.4.3 Interaction

Having dealt with supply and demand, it is also important to consider the distance deterrence term, since this variable controls consumer interaction between demand and supply and thus generates model predictions that are consistent with known patterns of consumer flows. Traditionally, these models have been developed using straight line distance, though Clarke *et al.* (2006) note that widespread car ownership and the inconvenience of carrying food shopping means that access to grocery stores by car is important, and thus road travel time becomes an important concern. To this end, Birkin *et al*. (2010a) note that in their experience of applied model building, straight line distance rarely works, instead recommending that a road network and associated road travel times are needed in order to accurately model flows between origins and destinations. Given the rural nature of Cornwall, it is considered realistic to assume that a majority of interactions between supply and demand will be driven by trips using road transport. As a predominantly rural area with poor infrastructure and heavy congestion, travel times between geographically proximate locations may be lengthy, especially on the coastline where long diversions inland may be needed to travel from one headland to the next.

The road travel times used here were provided by Sainsbury's and extracted from MapInfo Drivetime (version 7.1) software using the 'Street Pro' (2011 edition) road network. Based on Sainsbury's usual approach, 'out-of-the-box' settings were used (e.g. no user defined speed matrices were applied) and the quickest off-peak route (rather than the shortest) was

applied. The drive time software itself is a powerful tool for calculating drive times, taking account of routing restrictions such as roads with limited access/exit restrictions, long-term roadworks and traffic signals. Birkin *et al*. (2010a) note that such drive time matrices should be used with care, particularly surrounding variations between peak and off-peak travel times, congestion etc. Notwithstanding this limitation, the travel times within the supplied matrix appear reasonable and generally realistic, based on the author's own knowledge of the study area. Given the impact of the coastline on journey times for relatively short point-to-point journeys, it is believed that the use of drive-time data ensures that the distance deterrence term is better able to reflect accurately the relative accessibility of stores from consumers' residential locations, workplace or overnight accommodation. Given the applied nature of this research, it is also important to ensure that the approach used represents that which is commonly applied in industry. Since this data was sourced from Sainsbury's, using the settings that they would commonly employ – and justify within their own store forecasts – it is considered to be a highly appropriate data source to represent the distance deterrence term.

In conjunction with these travel times, the model allows different β values to be used in order to simulate the ability of different consumers to travel further to their store of choice. Birkin *et al*. (2010a) suggest that this could vary based on car ownership (reflecting relative ability to travel further), or by income or socio-economic status, recognising that certain types of consumer may be both able (i.e. are more likely to own a car and thus have greater mobility) and willing (in terms of disposable income) to travel further to the store of choice. Within this disaggregated model, β varies by household type, using the OAC classification as a proxy for both income and car ownership. Higher income households who are more likely to own cars can be given the 'freedom' to travel further to their store of choice, passing relatively less attractive stores on their way. For example, research has identified that consumers who shop at Sainsbury's (which has a more upmarket position than some of its competitors) show a tendency to have driven past an alternative store close to their home in order to reach a Sainsbury's (MINTEL, 2012).

In contrast, low income groups with access to transport may display a greater propensity to travel in order to access discount stores, potentially avoiding higher end stores that are geographically proximate to their origin (Fotheringham and Trew, 1993). Conversely, less mobile groups may be more likely to shop at their closest store even if it does not represent the brand that is most attractive to their income or socio economic group. The model acknowledges that different consumers will exhibit different abilities and willingness to travel and that within each group of consumers this will also be driven by the attractiveness of the brand or store available.

Three β values have been applied, representing the behaviour of high, mid and low income consumers. These are based on the OAC classification once again and are drawn from Thompson *et al*.'s (2012) study of consumer grocery shopping habits and interaction patterns

in Yorkshire and The Humber. Thompson uses Acxiom survey data to identify consumer interactions between their home address and their stated grocery store. Using road travel time at the postal sector level, he identifies average travel distance for consumers within three income categories, and uses this to apply appropriate β values within his model in order to capture the propensity (through either choice or need) for higher income consumers to travel further than lower income consumers. Within this application of the SIM, the relative difference between Thompson's high, medium and low income β values has been used to set β to account for differences in interaction behaviour.

Consumers have been categorised into income groups based on the OAC classification of their home neighbourhood. The Living Costs and Food Survey (LCF) [24] identifies household expenditure by OAC group, recognising that household purchasing power and spending characteristics are influenced by their socio-economic and geodemographic characteristics (see Chapter 5). Consumers have been grouped into three income classes for use in the modelling (Table 6.4), using surveyed household gross weekly income for each OAC supergroup (see Chapter 4 for more detail on the household level characteristics within each OAC group).

Table 6.4 - Categorisation of consumers into income groups

Income Group	OAC Supergroup	Average weekly gross income
High Income	2 – City living	£962.70
	4 – Prospering suburbs	£857.30
Mid Income	3 – Countryside	£851.90
	6 – Typical traits	£710.00
	7 – Multicultural	£693.50
Low Income	1 – Blue collar communities	£536.20
	5 – Constrained by circumstances	£428.80

Based on Thompson's analysis, the β value for high income consumers is set proportionately lower than that for the mid-income consumers, and for low income groups β maintains a value which is proportionately higher than the corresponding value for the mid-income groups. It is thus the β value for mid-income consumers which calibration seeks to estimate. Having outlined the characteristics of the model and input data, sections 6.5 to 6.6 seek to calibrate and validate the model with reference to Sainsbury's store data and then

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[24] Table A53 (Average gross normal weekly household income by OAC supergroup, 2011)

demonstrate that the model can be used to estimate store-level revenues with greater accuracy.

6.5   Model calibration

The process of model calibration seeks to set model parameters in such a way that the model is able to reproduce existing consumer behaviour to an acceptable level of accuracy. If observed behaviour can be consistently replicated by the calibrated model, the model can be used in a predictive capacity; for example to consider the impact of new store openings with confidence. To calibrate, some form of observed flow data is required and this can be used to assign values to parameters such that the model outputs minimise the difference between observed and predicted flows. In practice calibration involves setting model parameters to optimize one or more conditions that are thought to be representative of flow patterns, in this case average trip distance (ATD) outlined in section 6.5.2. Since the model is non-linear in nature, application of 'standard' techniques, such as regression, to estimate model parameters is not possible (Wilson, 1971). Measures of goodness-of-fit (GOF) are then used to validate and test the degree of statistical fit between the observed and predicted data. This section first considers the required data for calibration and validation (see Fotheringham and Knudsen, 1987; Knudsen and Fotheringham, 1986; and Openshaw, 1975 for more detail).

6.5.1   Data for calibration

Effective calibration is dependent upon the availability of sufficient observed customer flow data. Obtaining observed flow data can be tricky and inevitably involves generalising from a sample of customers which, at best, tends to represent one retailer's clients rather than the entire market. This thesis greatly benefits from access to data derived from Sainsbury's Nectar loyalty card, which is a useful tool for model calibration. The calibration data has been derived from individual transaction level records for all transactions involving a loyalty card in the four study stores of interest (see Chapter 4 for more detail on the loyalty card dataset). Sainsbury's own in house analysis, based on their knowledge of market penetration and Nectar card uptake, has generalised these recorded Nectar flows which are used to estimate their store revenue derived from each OA. This data effectively represents the flow of consumer expenditure from each OA to each store. It is these flows that have been used as observed flows for model calibration (aggregated to LSOA level to reduce the effect of very low flows from some OAs), and it is from these flows that observed ATD has been calculated.

The great benefit that this consumer level data brings to the thesis, and in particular for calibration, has been noted throughout. It should be recognised, however, that there may be some bias introduced by assuming that all flows in the model, including flows to other retailers, can be calibrated with reference to data from one retailer. As noted in section 6.3, it is recognised that flows will be driven by the relative attractiveness of different brands,

which is not captured within the Sainsbury's data. The use of the alpha parameter here, which has been set entirely independently with reference to consumers' stated behaviour in the Acxiom ROP, should go some way to account for this brand preference.

Since this study does not have access to any form of reliable surveyed data for consumer brand preference in Cornwall, attempts have not been made to calibrate the model through variation within the alpha parameter (although some experimentation was undertaken in order to determine the appropriate magnitude for the alpha value). Any attempt to fit the alpha values to the Cornwall flow data (which is limited to one retailer and four stores) would represent too much of an attempt to fit the model to the observed data, which Birkin *et al.* (2010a) term 'over-paramatization'. It would be all-to-easy to artificially alter the alpha values such that the model exactly replicated the observed Sainsbury's flows for the study stores, but with absolutely no regard for actual consumer behaviour. Nonetheless, the impact of incorporating brand attractiveness has been assessed and is addressed in section 6.5.2.

Calibration of β will take place with reference to the average trip distance and validated using selected GOF statistics. The model's overall performance will then be considered in terms of its ability to replicate observed store revenue (section 6.7).

6.5.2 Model calibration using average trip distance (ATD)

The distance deterrence parameter (β) allows predicted consumer flows to be controlled, determining the importance of distance/travel 'cost' in consumer decision making behaviour. Birkin *et al.* (2010a) identify that calibration of β is traditionally undertaken by comparing observed and predicted ATD. Batty and Mackie (1972) assert that this is the most appropriate calibration statistic to use for a SIM which employs an exponential distance function. The premise is simple: if the model can replicate observed consumer trip making characteristics (such as the average distance travelled or other travel 'cost') then it is likely to estimate the spatial patterns of trade (or store catchment area) effectively. Assuming that demand estimates are reasonable, and that the model has an appropriate representation of store attractiveness, actual expenditure flows to stores, and thus individual store revenue should then represent reality as closely as possible. Equation 6.10 outlines the calculation used to minimise the difference between observed and predicted ATD:

$$ATD = \frac{ATD^{Pred}}{ATD^{Obs}} \qquad (6.10)$$

Where:

$$ATD^{Pred} = \frac{\sum_{ij} S_{ij} C_{ij}}{\sum_{ij} S_{ij}} \qquad (6.11)$$

$$ATD^{Obs} = \frac{\sum_{ij} \hat{S}_{ij} C_{ij}}{\sum_{ij} \hat{S}_{ij}} \qquad (6.12)$$

and S_{ij} represents predicted flows, and $\hat{S}_{ij}$ represents observed flows.

The spreadsheet based model, developed by the author, iterates through a series of β values, recording the associated ATD, with a view to minimising the difference between ATD^{Pred} / ATD^{Obs}. Since the model operates using road travel time in place of distance, ATD can be thought of as the average trip 'cost', and reflects the average travel time (in minutes) (Table 6.5). The observed ATD or cost has been calculated using Sainsbury's transaction level data, linked to consumers' loyalty cards, reported at an OA level. Comparison of ATD based on road travel time in Table 6.5 identifies a close correspondence between predicted and observed ATD, with a trade-off between the slight over-estimation at Newquay and under-estimation at Truro, which, due to its size and location on the major road network, is able to draw consumers from a wider trade area.

Since the Nectar card dataset is characterised by a number of OAs with very low flows (often representing only a handful of customers), the Sainsbury's data (and corresponding model flows) have also been aggregated to LSOA level (to reduce the impact of very low flows) for use in calibration and validation. Since road travel time data is not available at the LSOA level, the ATD at the LSOA level reflects actual (straight line) distance, calculated using centroid co-ordinates from each LSOA, and co-ordinates derived from individual store postcodes. Table 6.5 shows also the observed and predicted ATD based on LSOA travel time on a store-by-store basis, demonstrating a close association between ATD^{Pred} and ATD^{Obs}, and again highlighting the trade-off between Newquay and Truro.

The ability of the model to predict ATD such that it closely resembles observed ATD suggests that the model parameters set are appropriate. In particular, ATD can be used to identify the effectiveness of incorporating alpha as a parameter. As identified in section 6.3.2, alpha is intended to control the relative attractiveness of different brands to different household types, based on income. Following the introduction of alpha as a model parameter it is expected that higher end retailers, such as M&S, Waitrose and Sainsbury's will be more attractive to high income households and less attractive to low income households, whilst discount retailers (such as Lidl, Aldi, Iceland and, to an extent, ASDA) will be relatively more appealing to low income households. Therefore high income consumers should be willing to travel further to visit higher end retailers, and low income consumers are expected to exhibit a willingness to travel further to reach a discount retailer, notwithstanding the fact that β has been set to increase the impedance of distance for low income consumers. In order to identify the impact of alpha on consumer flows (as measured by ATD), Table 6.6 shows the average predicted travel time for low and high income consumers under two scenarios: one where alpha is equal to one (as such it has no impact on modelled flows); and secondly where alpha varies based on the store and household income combination.

Table 6.5 - Observed and predicted ATD (travel time and straight line distance) for Cornish study stores.

Based on 52 week flows.

ATD	Road Travel Time (Minutes) – OA Level			Straight line distance (km) – LSOA Level		
	ATD^{Pred}	ATD^{Obs}	$\dfrac{ATD^{Pred}}{ATD^{Obs}}$	ATD^{Pred}	ATD^{Obs}	$\dfrac{ATD^{Pred}}{ATD^{Obs}}$
Newquay	9.91	8.84	1.12	2.73	2.30	1.19
Bude	10.70	10.27	1.04	3.76	3.34	1.13
Bodmin	12.16	11.70	1.04	5.99	5.36	1.12
Truro	25.80	27.34	0.94	6.81	7.20	0.95
Average	**14.64**	**14.54**	**1.04**	**4.87**	**4.55**	**1.11**

Table 6.6 clearly demonstrates that the incorporation of alpha values (from Table 6.3) improves the ability of the model to replicate the type of consumer behaviour anticipated. Considering low income consumers, the use of alpha values (that vary by consumer income and brand type) increase these consumers' average travel time to an ASDA store by over 9 minutes (compared to $\alpha = 1$), suggesting that the model can now account for the fact that these consumers are willing to travel further to reach ASDA stores, which become relatively more attractive, by-passing stores that are geographically proximate in order to do so. Similarly, high income consumers exhibit increasing willingness to experience longer average travel times (increasing by around 50%) to shop at M&S, and considerably reduced average journey times for visits to ASDA, for example.

Table 6.7 considers individual brands/retailers' countywide market shares, shown before and after incorporation of the alpha parameter. In common with Table 6.6, market share analysis identifies that the inclusion of relative brand attractiveness by income group generates market shares in line with expectations. For example, discount retailers such as Aldi and Lidl, and those more focussed on price (e.g. ASDA) exhibit higher market shares among OAs classified as low income following the introduction of the alpha parameter. Table 6.5 to Table 6.7 suggest that the model can replicate observed ATD, accounting for expected behavioural characteristics associated with household income and brand attractiveness. Section 6.6 seeks to assess model performance more broadly using GOF statistics.

Table 6.6 - Impact of alpha parameter on ATD for low and high income consumer groups

Retailer	Low income consumers		High income consumers	
	$\alpha = 1$	α varies by k and n	$\alpha = 1$	α varies by k and n
Aldi	6.80	6.69	6.90	5.17
ASDA	21.83	30.86	25.21	15.83
Lidl	11.39	11.61	9.65	7.00
M&S	4.88	4.02	3.73	6.83
Morrisons	20.65	24.97	16.46	18.40
Sainsbury's	23.03	15.91	19.79	26.62
Tesco	29.89	25.50	22.64	29.31

Table 6.7 - Impact of alpha parameter on retailer market shares

Retailer	Low income consumers		High income consumers	
	$\alpha = 1$	α varies by k and n	$\alpha = 1$	α varies by k and n
Aldi	3.3	3.0	4.3	3.0
ASDA	14.0	21.7	22.3	13.8
Lidl	10.3	10.5	9.2	6.3
M&S	1.3	0.7	1.5	3.2
Morrisons	14.8	19.7	10.5	11.3
Sainsbury's	14.3	8.1	15.8	23.8
Tesco	27.1	20.4	22.3	28.6

6.6 Model ability to replicate known flows

Having calibrated the model to replicate known characteristics of consumers trip making behaviours via ATD, the focus now turns to assessing the model's overall performance. This is achieved by validating its ability to reproduce the known flow data supplied by Sainsbury's for four stores of interest. Knudsen and Fotheringham (1986) note that this assessment of the model's ability to replicate an observed set of data is an important

component of model building. Validation via GOF statistics is based on measuring the differences between observed and predicted values (Batty and Mackie, 1972). This section makes use of two GOF statistics: R^2 (or the coefficient of determination) which is commonly used to assess SIM performance, and SRMSE (standardised root mean square error). These are both considered to be some of the 'better performing' and more commonly used GOF statistics (Fotheringham and O'Kelly, 1989). SRMSE is observed to be very sensitive to any differences between the observed and predicted flow matrix (Harland, 2008).

SRMSE is calculated as shown in equation 6.13. A value of zero represents a perfect fit between observed and predicted matrices (Knudsen and Fotheringham, 1986), with an upper limit generally accepted to be 1, though Harland (2008) illustrates that the upper limit can rise above 1 under certain conditions in a sparsely populated matrix where a number of zero flows exist.

$$SRMSE = \frac{\sqrt{\sum_i \sum_j (S_{ij} - \hat{S}_{ij})/m \, x \, n}}{\sum_i \sum_j S_{ij}/m \, x \, n} \qquad (6.13)$$

As previously, S_{ij} represents predicted flows, $\hat{S}_{ij}$ represents observed flows and $m \, x \, n$ represent the dimensions of the observed and predicted LSOA (i) to store (j) flow matrix.

Harland (2008) notes that the SRMSE does a good job of identifying discrepancies between observed and predicted flows in a number of different scenarios, all of which he simulated on a dataset in order to evaluate the sensitivity of different GOF statistics. He noted that under all his scenarios (which involved either altering the magnitude of flows or shifting flows to alternative origin/destination cells) the SRMSE picked up that differences existed between S_{ij} and $\hat{S}_{ij}$. By contrast, R^2, outlined in equation 6.14, was found to be sensitive to values that had been shifted elsewhere on the matrix, but less sensitive to differences in the volume of individual flows when they appeared in the correct cells in the matrix. Nonetheless, both are valuable tools in assessing model performance and have been utilised here.

R^2 is calculated as follows:

$$R^2 = \left[\frac{\sum_i \sum_j (S_{ij} - \overline{S_o})(\hat{S}_{ij} - \overline{S_p})}{\sqrt{\sum_i \sum_j (S_{ij} - \overline{S_o})^2 \; x \; \sum_i \sum_j (\hat{S}_{ij} - \overline{S_p})^2}} \right]^2 \qquad (6.14)$$

Where, $\overline{S_o}$ represents the mean of all S_{ij}'s (predicted flows) and $\overline{S_p}$, represents the mean of all $\hat{S}_{ij}$'s (observed flows). R^2 is bounded by an upper limit of 1 (Knudsen and Fotheringham, 1986).

Table 6.8 shows the SRMSE and R^2 values for the disaggregate model, for the four calibration/validation stores.

Recall that an SRMSE of 0 and R^2 of 1 would denote an exact fit between observed and predicted values. Table 6.8 clearly identifies that the model is performing well, with reference to the four study stores, demonstrated by an overall SRMSE of 0.05 and R^2 of 0.88. On a store-by-store basis, the model is able to replicate flows to the Newquay store most accurately. All stores exhibit an R^2 of above 0.84, and, with the exception of Bude, an SRMSE of 0.1 or lower, suggesting that both the spatial distribution of flows, and the magnitude of individual flows, correspond closely with the observed values. The Bude store exhibits a higher SRMSE of 0.2, suggesting that, whilst the spatial pattern of flows shows a close match to observed data ($R^2 = 0.86$), the volume of modelled flows show some disparity with observed flows. The characteristics of this store make it tricky to model. It is a popular, but very modestly sized store (11,500 square foot) serving a thriving town centre and seasonal tourist trade. Based on their experience at Tesco and Sainsbury's, Wood and Tasker (2008) acknowledge that smaller format supermarkets such as the Bude store are trickier to model using a SIM as they tend to have a smaller catchment than larger supermarkets. Sainsbury's own analysis also identifies that only 58.7% of store spend (2010 trading year) was associated with a Nectar card, and thus the flow data at this store is more limited. In spite of this, section 6.7 demonstrates that modelled flows can be used to predict seasonal variations in revenue at this store to an acceptable level of accuracy.

Table 6.8 - GOF statistics for four Cornish study stores.

Based on 52 week average flow data

	SRMSE	*R²*
Newquay	0.08	0.93
Bude	0.20	0.86
Bodmin	0.10	0.84
Truro	0.08	0.84
Overall[25]	**0.05**	**0.88**

The application of GOF statistics goes some way to validate the model's ability to replicate known flows and thus assess how well the model has been specified (and the assumptions made). Nonetheless, the GOF statistics are only indicative of the models' performance. To understand more about any differences between observed and predicted revenue, especially at the coastal resort stores (which are subject to greatest seasonal variations) flows should be considered spatially. Figure 6.2 demonstrates the spatial pattern of observed and predicted flows within the catchment area of the Newquay store. It is clear that there is a good spatial

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[25] Not averaged from individual store values but calculated based on observed and predicted matrix for all four stores.

fit between observed and predicted flows, with the model showing a tendency to predict within 10% of reality in most OAs, with some over prediction in OAs in close proximity to the store. Figure 6.3 begins to consider the predicted inflow on a month-by-month basis, again at the Newquay store. As reasonably expected, April (fringe season) and August (peak season) demonstrates a higher inflow from a fairly wide catchment, incorporating inflow from a number of rural and coastal output areas to the south of the town, which are home to much of the visitor accommodation within this store catchment. In January, when much of this accommodation is closed or operating well below capacity, the spatial pattern of trade around the store produces a noticeably tighter core catchment area.

Since residential and visitor demand are handled separately within the model, it is also possible to consider the total inflow from local residents and also from visitors. Figure 6.4 considers June 2010 and demonstrates, on an OA-by-OA basis, the inflow from residential and visitor demand. It is clear that visitor demand exhibits a greater degree of concentration around the resort of Newquay itself, driven by the location of visitor accommodation, which, as explored in Chapter 5, is concentrated around resorts such as Newquay, with a number of OAs generating over £5,000 per week inflow from visitor demand alone. By contrast, and as expected, residential demand is drawn more uniformly from the OAs that make up the store catchment, with distance decay, driven by drive time, more pronounced.

This brief exploration of flow patterns at the Newquay store highlights that the model appears to be performing well, replicating observed flows and producing flow patterns which are consistent with the input data and assumptions made, and clearly highlighting the impact of seasonal variations driven by tourism. The real value of the model is its ability to predict store revenue with accuracy, such that it can be used in a predictive capacity. Birkin *et al.* (2010a) actually suggest a move away from traditional concepts of goodness-of-fit statistics to a more complex approach to model validation, considering whether the models are able to accurately replicate customer flows and store revenue, effectively termed goodness-of-forecast and considered in section 6.7.

6.7   Model ability to estimate revenue

Since the model is intended for use in an applied, predictive capacity, the ability to generate accurate revenue predictions at the store-level is crucial. Revenue estimation is considered in terms of the four stores used for calibration, and an additional 'test store', that has not been part of the calibration process (and for which limited data is available). It is also through revenue estimation that the impact of incorporating visitor demand can be evaluated, since seasonal variations are reflected in the store's weekly revenue data. Since flow data is not available for visitors, it is impossible to incorporate visitor demand in model validation based on observed and predicted flows, and reference to recorded store revenue and seasonal sales fluctuations is the only way to assess the impact of the inclusion of visitor demand.
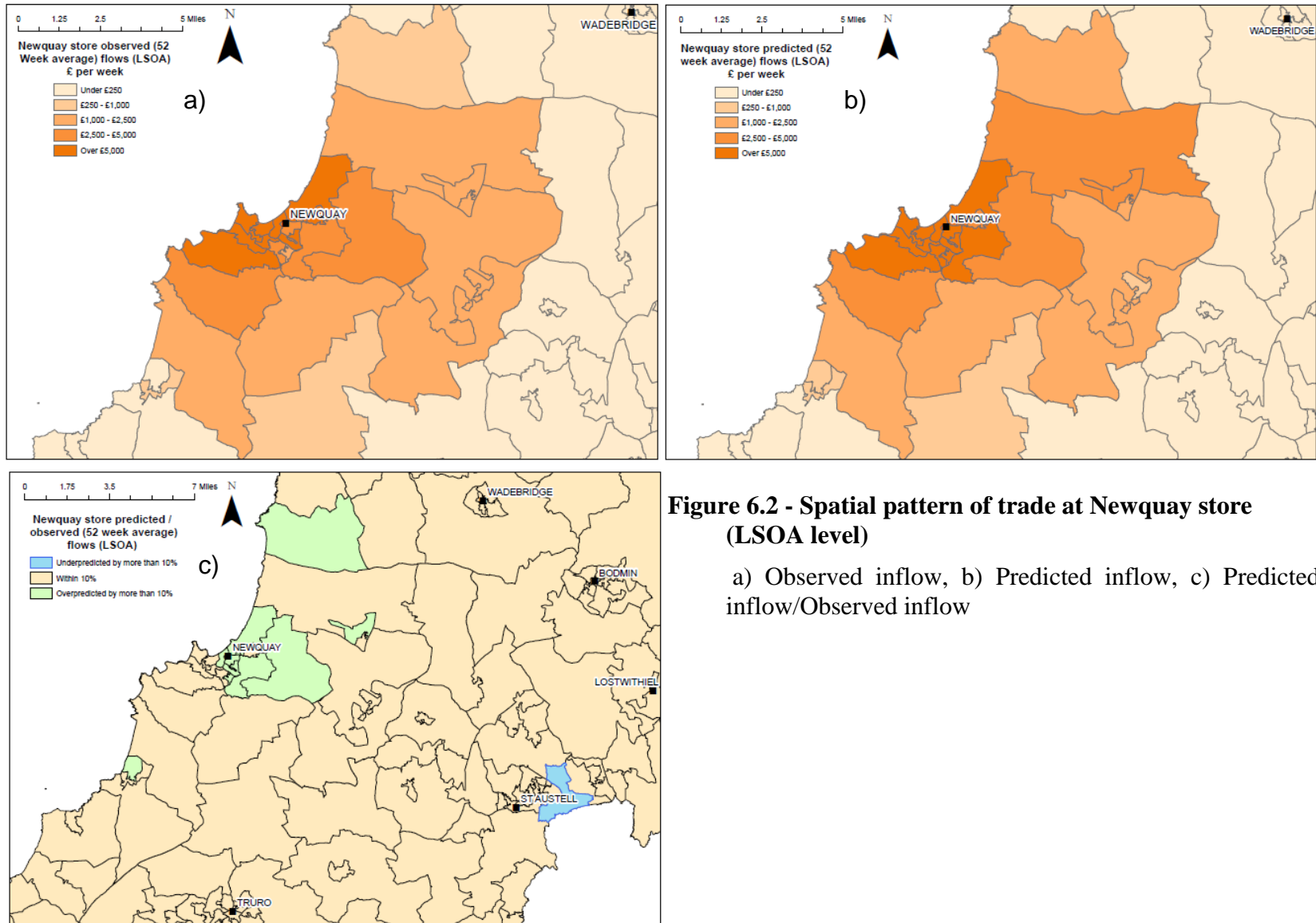
Figure 6.2 - Spatial pattern of trade at Newquay store (LSOA level)

a) Observed inflow, b) Predicted inflow, c) Predicted inflow/Observed inflow
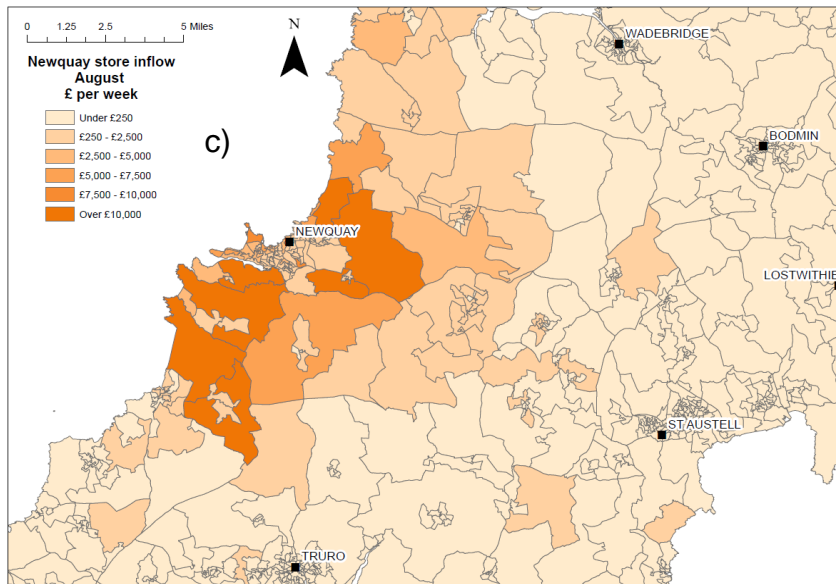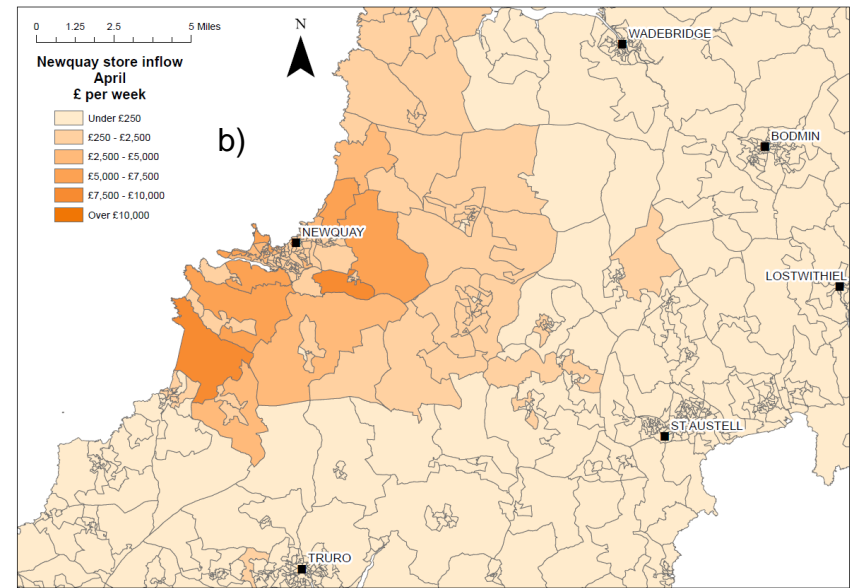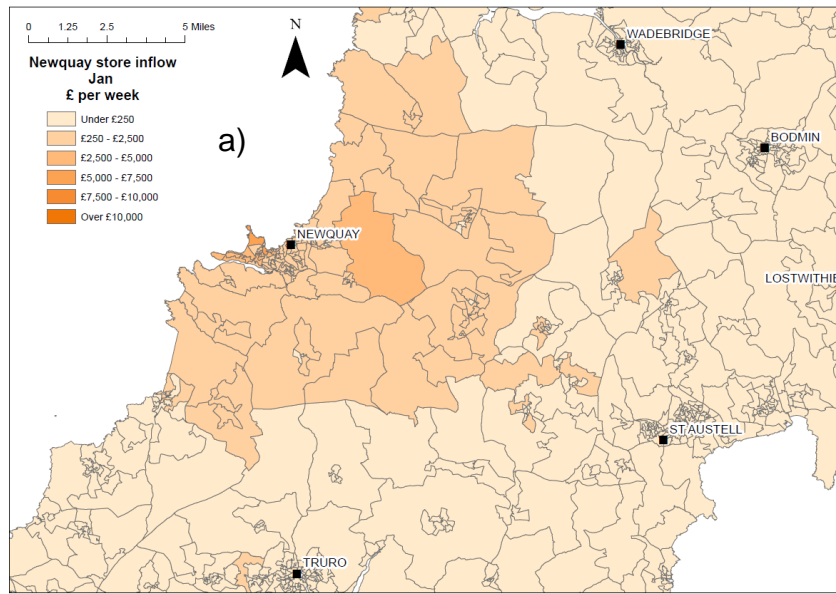
Figure 6.3 - Newquay store inflow at the OA level (residential and visitor demand).

Average weekly inflow (£) in a) January, b) April and c) August
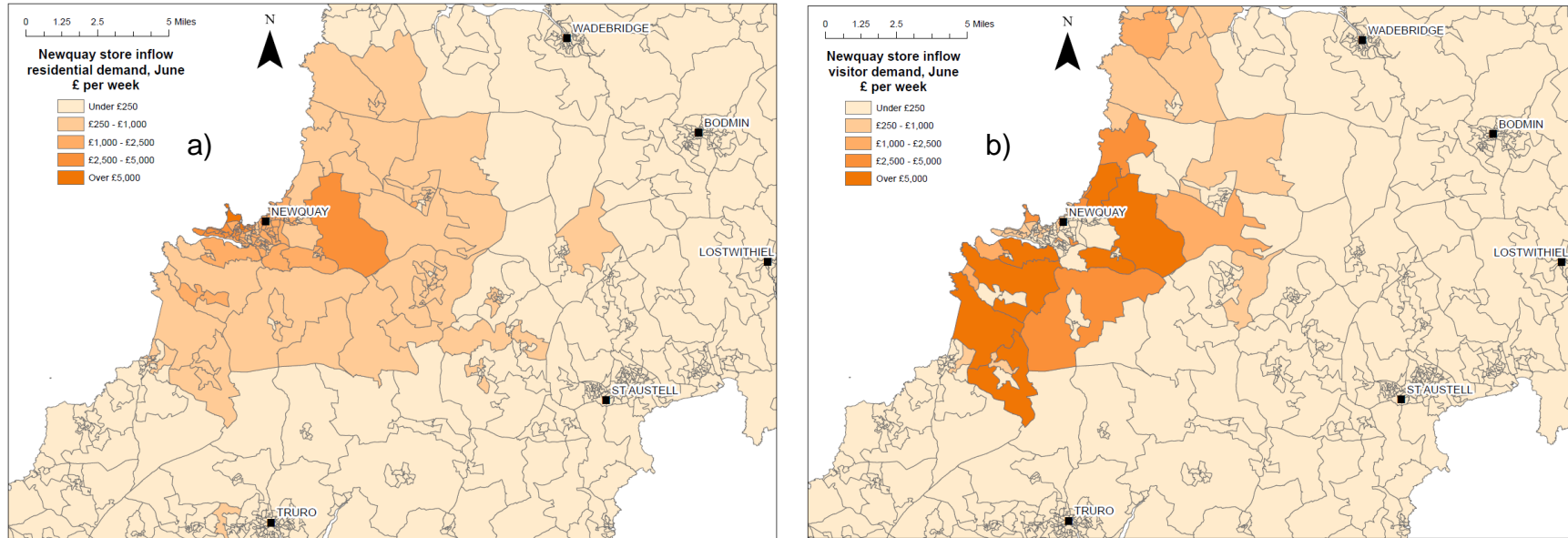
Figure 6.4 - Spatial pattern of trade at Newquay store at OA level.

a) Average weekly inflow in June (local residential demand), b) Average weekly inflow in June (visitor demand)

The revenue data used here has been supplied by Sainsbury's and considers store-level revenue, derived from food and drink sales, on a week-by-week basis, as used in Chapter 4. Since expenditure estimates are available on a month-by-month basis, the recorded weekly store revenue has been averaged on a month-by-month basis. Additional store revenue information has been extracted from the Cornwall Retail Study (CRS) and from Sainsbury's own estimates of competitor store revenue and performance. It was previously noted that this form of insight into retailers store revenue is frequently unavailable for academic investigations and again highlights the importance of this study. Store revenue can be estimated by summing all flows terminating at a given store. Table 6.9 shows the ratio of observed to predicted store revenue for the four study stores on a month-by-month basis, derived using the disaggregated SIM. As previously stated, a value of 1.0 demonstrates exact correspondence between observed and predicted store revenue, a value above 1 demonstrates that the model has over-predicted revenue, whilst a value of less than 1 demonstrates an under-prediction.

It is clear that the disaggregation on both the demand and supply side has impacted upon modelled store revenue, especially at the stores in Newquay and Bude. With the exception of March, November and December (impact of Christmas and Easter spending uplift), the less seasonal Truro and Bodmin stores are consistently predicted to within 10% of reality (and often to within 5%), suggesting that the model is generally working well. Most notably, the degree of under-estimation has reduced considerably at Newquay and Bude, often representing a slight over-estimation, especially earlier in the year. With the exception of December (impact of Christmas spending uplift), modelled revenue is consistently within 10% at Newquay, and within 5% for much of the tourist season. The degree of variability in terms of the monthly ratio of observed to predicted revenue has reduced markedly for Bude, and whilst the model overestimates revenue at the Bude store by 14% in both January and February, the model is able to predict revenue to within 10% of observed revenue from March through to November. Figure 6.5 explores the observed and predicted revenue on a month-by-month basis at Newquay and Bude. Whilst actual revenue has not been shown (in order to preserve the confidentiality of store trading data), it is clear that the predicted seasonal revenue fluctuations correspond very closely with the observed seasonal trade pattern, again suggesting that the model is operating well.

The comparison of observed and predicted revenue on a month-by-month basis should, however, be treated with some caution. Since the observed data is based on a month's worth of trading (average of 4 or 5 weeks recorded revenue) short term revenue fluctuations driven by promotions, local roadworks or specific events in-store and nearby (or even in competitors stores) can all drive very short term fluctuations in store revenue that could not possibly be predicted by the model, and which would not usually be noticed when considering average weekly revenue on an annual basis. For example, whilst Bude is over-estimated by 14% in January, the corresponding predictions for Newquay, Bude and Truro

are all within 3% of reality, suggesting that the model is working well and that a locally contingent factor to that store during one or more trading weeks in January 2010 contributed to lower than expected in-store sales.

Table 6.9 - Ratio of observed to predicted store revenue (predicted/observed) for Cornish study stores using disaggregated SIM

2010 Data	Newquay	Bude	Bodmin	Truro	Average
52 WK Ave	0.99	1.00	0.97	0.98	0.99
Jan	1.00	1.14	1.01	0.99	1.04
Feb	1.02	1.14	0.96	0.96	1.02
Mar	0.97	1.06	0.87	0.89	0.95
Apr	1.07	1.10	1.04	1.04	1.06
May	1.06	1.07	0.99	0.98	1.03
Jun	1.05	0.99	0.98	1.04	1.02
Jul	0.99	0.94	0.97	1.06	0.99
Aug	1.02	0.91	1.00	1.10	1.01
Sep	0.97	0.95	1.00	0.98	0.98
Oct	0.93	0.92	0.98	0.96	0.95
Nov	0.91	1.02	0.92	0.86	0.93
Dec	0.88	0.88	0.82	0.75	0.83
Max	1.07	1.14	1.04	1.1	1.05
Min	0.91	0.91	0.87	0.86	0.89
Range	0.16	0.23	0.17	0.24	0.16

Note: **Max**, **Min** and **Range** exclude December (Christmas uplift)

$R^2 = 0.88$ SRMSE = 0.05

If the model was witnessed to consistently under-estimate or over-estimate revenue at certain times of year in all four stores (e.g. April), it would be tempting to return to the input expenditure estimates and seek to boost or suppress demand at that time of year. Whilst this may deliver slightly improved revenue estimations for the four study stores during the specific time period, this approach would not deliver a more accurate model, since demand would have been artificially modified to reflect supply side constraints at only a subset of stores, with no clear understanding of the impact on other stores. It is impossible to identify

Seasonal store revenue predictions at Newquay and Bude Sainsburys
Observed and predicted revenue
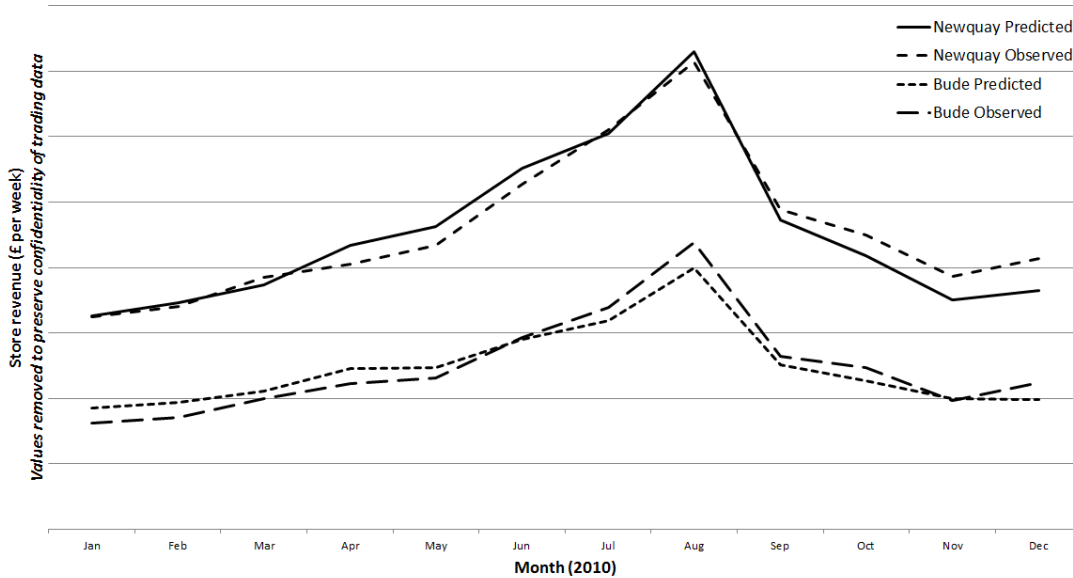
Figure 6.5 - Observed versus predicted store revenue at Newquay and Bude stores

whether slight under or over estimation at the four study stores represents an under-estimation of demand or factors specific to Sainsbury's (such as in-store offers or promotions by Sainsbury's or a competitor). Modifying individual demand layers to fit limited supply side observations would represent an attempt to over-calibrate the model to match a limited range of flows or observations, and would not be possible when used in a predictive capacity for new store investments or with other retailers, where such information is not available.

6.7.1   Revenue estimation against additional test stores

It is the ability of the model to predict expenditure flows and subsequent store revenue for other stores and operators that represents the crucial test of model accuracy. Birkin *et al.* (2010a) note that "undertaking predictive experiments is the only realistic way to prove that models work". Typically, these predictive experiments involve testing the predictive capacity of the model against additional stores for which data is held, but which have not formed part of the model development or calibration. In this case, such data is held for an additional store at Falmouth in Cornwall.

Falmouth is not considered to be a coastal resort, yet the maritime town is popular with tourists. The store is around 30,000 Sq Ft and located on an out of town site. The store is a former Co-Op, operated by Sainsbury's since October 2009 and so store trading figures must be used with some caution, since they may not reflect the long term trading potential of the store. Nonetheless, they can be used as an indicator of store performance for comparison with modelled outputs. Considering the entire 2010 trading year (52 week average), the model is seen to slightly underestimate revenue at the Falmouth store, predicting 96% of the recorded store-level sales. This is considered to indicate very good model performance and gives some confidence in the models ability to predict revenue at stores which have not been

used as part of the calibration process. Furthermore, this slight underestimation may reflect the 'novelty value' of the store's recent acquisition by Sainsbury's, driving a short-term sales uplift as consumers try the new store, or are attracted by increased promotional activity that often coincides with a new store opening (Birkin *et al.*, 2010a)

The inclusion of the Falmouth store demonstrates that the model can predict revenue with accuracy at an additional Sainsbury's store that did not form part of the model calibration. It is also important to identify that the model is able to achieve a similar level of accuracy for competitor stores. One of the main uses of the model in a predictive capacity will involve simulating new store openings and identifying the impact on consumer flows for all retailers, in order to explore changes in market share and spatial patterns of trade diversion. No flow data is held for non-Sainsbury's stores, but some indication of average weekly revenue is available from Sainsbury's own estimates of competitor performance and from a county-wide retail study. Bodmin, Bude and Newquay all have a Morrisons store within their catchment. Revenue estimations are available for these stores from Sainsbury's own in-house analysis (relating to 2010), and these estimates correspond closely to the estimates derived by GVA Grimley (2010) in the Cornwall Retail Study (CRS) based on their market share analysis derived from a 2009 household survey (Table 6.10). To preserve the confidentiality of Sainsbury's own in house model, only the average of the CRS and Sainsbury's revenue predictions for Morrisons stores are shown. In each case, the model is able to predict 52-week average revenue at these stores (which are all between 20,000 and 30,000 square foot) to within 5% of these additional predictions obtained from outside the model, suggesting that the model is performing well, particularly the application of alpha values, which seem to be able to reflect the strength of the Morrisons brand in this area.

Table 6.10 - Ratio of observed to predicted revenue predictions for selected Morrisons stores

Store	Predicted by Sainsburys and CRS (PredS)[26]	Predicted by Model (PredM)	PredM/ PredS
Morrisons Newquay	572,500	597,483	1.04
Morrisons Bude	437,116	446,015	1.02
Morrisons Bodmin	346,039	349,955	1.01

Given that the model is able to predict 52 week average revenue to within 5% of observed revenue at five Sainsbury's stores (Newquay, Bude, Bodmin, Truro and Falmouth) and matches external predictions at additional Morrisons stores, it is considered that the model is performing very well. In spite of some month-by-month over-estimation or under-estimation,

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[26] Average of CRS and Sainsbury's predictions

the model is able to provide robust revenue estimations (52 week average) which incorporate visitor demand and account for a range of demand and supply side characteristics, such as relative brand attractiveness. Weekly revenue estimations on a month-by-month basis have been demonstrated to be more tricky to model with observed data being very susceptible to short term sales fluctuations driven by locally-contingent factors that could not reasonably be incorporated in such a model. Whilst it must be acknowledged that month-by-month revenue predictions do not have the same level of accuracy as 52-week averages, the revenue predictions for Newquay and Bude still demonstrate that visitor demand estimates, in conjunction with a disaggregate SIM, can be used to identify seasonal variations in store-level sales and identify the magnitude of seasonal sales uplift, and predict store revenue, often to within 5-10% of observed revenue at different times of the year.

6.8 Implications and conclusions

This chapter sought to demonstrate that the small-area seasonal grocery demand estimates developed in Chapter 5, can be used in conjunction with a SIM to generate robust revenue predictions for grocery stores in tourist resorts. In their review and experience of applied spatial interaction modelling, Birkin *et al.* (2010a, p442) note that "models must be seen to work in the most obvious sense – they must reproduce known trip patterns and store revenues". Sections 6.5 - 6.7 have demonstrated, both statistically, spatially and in terms of revenue, that the disaggregate model is able to replicate known flows to a very acceptable level of accuracy. When considering 52 week average flows, the model can predict revenue to within 5% at eight stores for which revenue information is held. The stores in coastal resorts are inevitably far harder to model, not just because of seasonal demand fluctuations, but also due to the location of these stores within the centre of the popular Bude and Newquay resorts – offering car parking and other facilities in close proximity to the beaches, town centre and nearby attractions.

When considering flows and store revenue on a month-by-month basis the model has again been demonstrated to generally predict revenue to within 10% of observed values. It is acknowledged that there is some fluctuation in the accuracy of predicted revenue on a month-by-month basis. These fluctuations must be considered in light of the fact that modelling average weekly revenue on a month-by-month basis is more complex as unexpected and unexplained fluctuations in store trading data become apparent. Seasonal revenue estimation has highlighted that a range of local factors, that could not reasonably be incorporated in the modelling, may detract from its ability to predict monthly revenue to the same level of accuracy as annualised revenue predictions, where the impact of such factors is minimised by averaging revenue over a 52 week period. Nonetheless, the focus on average weekly revenue on a monthly basis is important in order to fully understand and account for the impact of visitor demand uplift on store sales, and the level of accuracy achieved by the

model is incredibly encouraging, especially given the many difficulties in estimating visitor numbers and associated spend outlined in Chapter 5.

Modelling visitor demand within a SIM remains challenging. In particular, the lack of flow data available to calibrate flows of visitor demand from their origins (generally visitor accommodation) to stores limits the ability to calibrate the model with reference to known flows driven by visitor demand. In particular, since little is known about the type of people occupying each unit of accommodation at any given time, and given that this changes on a night-by-night or week-by-week basis, it is difficult to incorporate brand attractiveness via the alpha parameter for visitors.

This thesis now seeks to apply this model in a number of supply side 'what if?' scenarios in order to demonstrate the impact of this form of modelling on location-based decision making and on the evaluation of the local economic impact of tourism. This is achieved through the introduction of additional stores into the model, drawn from current 'live' development schemes in Cornwall, in order to demonstrate the model's ability to predict new store revenue, impacts on competitors stores and changes in consumer flows. Incorporating visitor demand in a robust manner, as outlined in this chapter, allows retailers, developers and local planning authorities to take full account of the impact of new store development on the provision of viable retail services to meet the needs of residents and visitors alike, with a more comprehensive understanding of seasonal demand variations driven by tourism. Chapter 7 explores these 'What if?' scenarios in Cornwall.

Chapter 7: Using the SIM and visitor demand layer for network planning and new store development – case studies from Padstow, Looe and Newquay, Cornwall

7.1 Introduction

Chapters 1 and 2 sought to outline the role of location-based modelling in the strategic and operational decision making carried out by grocery retailers. It was evidenced that retailers struggle to incorporate all forms of seasonal non-residential demand within location-based decision making, especially for proposed investments (such as new store development) in highly seasonal coastal resorts, such as those in Cornwall (introduced in Chapter 4). It is recognised that grocery stores serving smaller coastal resort communities often provide much needed facilities and local services, supporting both residential populations and a seasonal influx of visitors. Visitor demand often improves the viability of a store in areas where residential demand alone may not be sufficient to support a store of that size, and may often result in seasonal demand fluctuations and subsequent over-trading during the peak tourist season. It is thus vital that retailers can accurately assess the trading potential of store developments in these destinations. This chapter seeks to demonstrate that the visitor demand estimates (Chapter 5), coupled with the disaggregate SIM (Chapter 6), can support location-based decision making, using examples from Cornwall.

The scenarios presented in this chapter directly address the needs of store location planners and local planning authorities in Cornwall. Live development schemes are considered from three major retailers (Morrisons, Tesco and Sainsbury's) in the resorts of Looe, Padstow and Newquay respectively. Throughout this chapter the disaggregate SIM is used in a 'What If?' capacity to assess various scenarios. These are focussed on the supply side – that is, changes are made to the provision of grocery retail facilities via the opening of new stores, whilst the demand side remains static. In this case, the model nominally represents the year 2010 based on the input demand side data (Chapter 5) and the supply side data used for calibration (Chapter 6), though supply side changes since 2010 have also been incorporated. Demand side changes relating to new accommodation provision and changes in holiday making behaviours are also considered separately, with reference to an alternative study area (Chapter 8).

The scenarios explored throughout this chapter have been chosen to highlight the capacity of the modelling framework in a variety of different contexts, such as to identify need for additional retail provision (Padstow), demonstrate trade claw-back/retention (Looe), and to evaluate the impact of new store openings on existing retailer market shares (Newquay) and subsequent network reorganisation that may be needed as a result. In all cases, stores are located in resorts where considerable seasonal fluctuations in demand, driven by tourism, are

evident. These scenarios thus highlight the importance of the modelling framework outlined in Chapters 5 and 6 in making complex location-based decision making that goes beyond simply estimating seasonal sales fluctuations in existing or proposed stores. This chapter argues that incorporation of visitor demand throughout the modelling process allows location planners, developers and local planning authorities a more complete evidence base for store development and local economic impacts in tourist resorts.

This chapter is organised as follows. Section 7.2 highlights the insight that modelling seasonal demand can generate, outlining the predicted seasonal sales fluctuations at Tesco's Padstow store. These fluctuations, coupled with trading intensities, are used to suggest the appropriate sized store for this catchment. Section 7.3 begins to consider new store development, modelling the impact of a new store to serve the coastal resort of Looe and identifying the resultant trade claw-back and the impact on existing retailers. Finally, section 7.4, which considers Newquay, seeks to model and assess potential network rationalisation plans following the introduction of a new large-format out-of-town store. Section 7.5 reflects on the impact of this form of modelling on location-based decision making in tourist resorts.

7.2   Using seasonal sales fluctuations to identify the need for additional retail provision – Padstow

7.2.1   Padstow

Padstow is a popular tourist resort and fishing port on the Camel Estuary, part of the north Cornwall coastline. Padstow experiences a considerable seasonal influx of visitors during the tourist season, boosting demand and supporting retail facilities and services far in excess of those that would be expected for a town of its size (population around 3,500). As outlined in Chapter 5, a number of holiday parks and other self-catering accommodation are located in the countryside and coastline surrounding Padstow, whilst the town itself is one of the most popular destinations in Cornwall for second home ownership. In addition to those visitors staying within or nearby the resort, a number of day visitors staying elsewhere in Cornwall visit Padstow, attracted not only by its harbour-side setting, but also by the many tourist art and craft shops and a number of well-known restaurants, including those owned by chef Rick Stein. In addition, Padstow is one of few navigable harbours on the north coast of Cornwall and is therefore popular for yachting. The long distance South West Coast Path, and popular Camel Trail also pass through the town.

Retail provision in Padstow comprises a modest Tesco store (10,500 Sq Ft), located on an edge-of-town site adjacent to the main A389 road link. The Cornwall Retail Study (CRS) (GVA Grimley, 2010) notes that this is the only store in the town that is suitable for a main food shop, with provision in the town centre limited to a 1,300 Sq Ft Spar store. Evidence from Tesco itself identifies that the Padstow store experiences considerable operational

challenges due to the highly seasonal influx of visitors to the resort, resulting in congestion within the store and car park. Tesco has taken temporary steps to address the issue of over-trading, locating a temporary 'seasonal/summer store' in a 500 Sq Ft marquee in the store car park during the summer months (April to September) (Maguire 2010). The store struggles to meet the needs of customers during the summer and needs additional floorspace to stock seasonal items and ease congestion in-store.

Anecdotal evidence from a former store employee (Employee A, 2011) in conversation with the author, supports this assertion, stating that the store not only struggles to cope with the volume of demand, but that the influx of wealthy holidaymakers and second home owners increases demand for certain product lines, generating further operational difficulties, exacerbated by the lack of space in-store. It therefore appears that the initial sales forecasts used to construct this store (which opened in the year 2000) underestimated the sales potential at this store and the resulting store is too small to fully meet the needs of the catchment, as evidenced by the requirement for additional floorspace during the summer months.

This section seeks to demonstrate that the SIM (developed in Chapter 6), used in conjunction with the visitor expenditure estimates (Chapter 5) can add considerable value to store location planning. The SIM can be used to identify seasonal sales fluctuations (driven by visitor demand) at the planning stage, such that appropriate stores and facilities can be developed. Actual sales figures for this store are not known and so the discussion which follows is based on modelled results. Chapter 6 evidenced that the calibration routine used has generated a model that is able to accurately estimate both the magnitude and seasonal variation within store trading characteristics.

7.2.2 Modelling seasonal revenue fluctuations at the Padstow Tesco store

Using the SIM, and incorporating both visitor and residential demand, the Padstow Tesco is estimated to attract an average weekly revenue of around £220,000 and a trading intensity of £20.83 per Sq Ft per week, rising to a revenue of almost £400,000 during the August peak, and a sales density of over £35 per Sq Ft per week (Figure 7.1). The estimated August sales density is in excess of the modelled performance of all other stores (by all operators) countywide. Tesco suggest that across their UK estate, stores achieved an average trading intensity of £24.87 per Sq Ft (Tesco Plc., 2012) and so the performance of this store during the summer far exceeds company average. It is likely that company average may be skewed by high performance of some of the smaller 'Tesco Express' and 'Tesco Metro' stores serving major urban areas, whilst the average trading intensity for stores of a similar size to Padstow may actually be slightly lower.
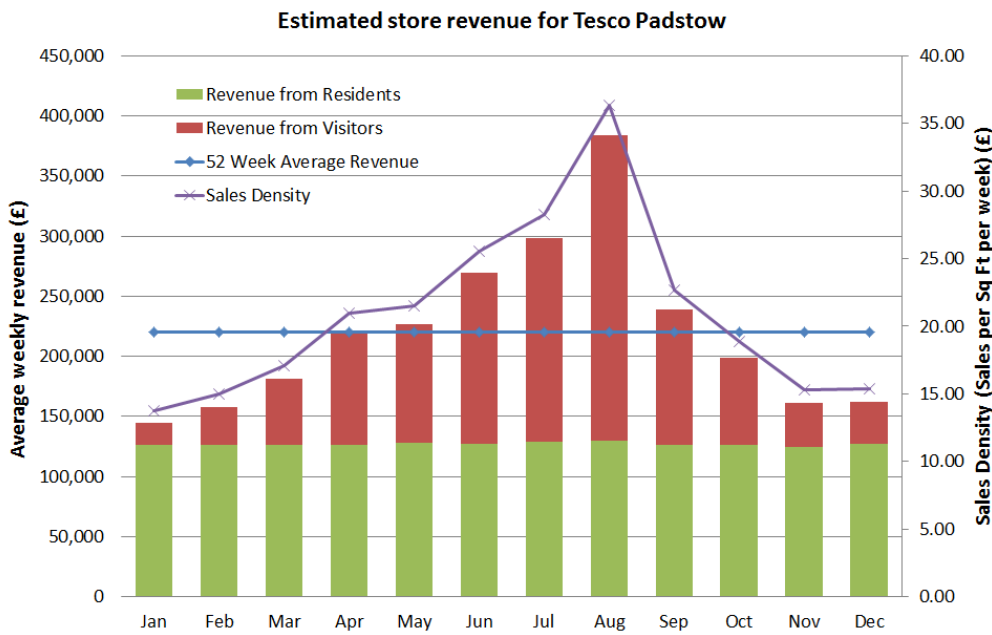
Figure 7.1 - Estimated store revenue and sales density for Tesco Padstow

It is evident from Figure 7.1 that the Padstow store over-trades considerably in the summer peak-season when levels of visitor demand (by value) exceed residential demand. Between June and August the store experiences trading intensities above £25 (per Sq Ft per week) and in August visitor demand is thought to account for over two thirds of the store revenue, with clear implications for in-store congestion, stock and staffing requirements. It is argued that this model forms an important operational tool, enabling retailers to understand the anticipated balance between residential and visitor demand at different times of year, in order to manage staffing, stock levels and the importance of different ranges in-store. The incorporation of visitor demand within the location-based modelling therefore affords retailers additional insight into the likely trading characteristics of new store investments that can inform operational decisions.

7.2.3   Identifying the optimum size for the Padstow store

Location planning teams face difficulty identifying the optimum size for new store investments in tourist areas. Even where visitor demand uplift can be identified, retailers have to decide whether to build a store that can easily cope with the seasonal demand uplift but may lack operational efficiencies during the low-season, versus development of a store that maintains an intended trading intensity year round, but which struggles to cope with demand uplift during the peak-season. In reality a balance must be sought. Given the availability of flexible, part time or seasonal labour, and the importance of providing a pleasant in-store experience for customers, it is suggested that here in Padstow, where seasonal uplift effectively lasts from April to October, longer term plans for this store should seek to increase floorspace.

Simulating floorspace increase at this store within the model allows location planners to identify the impact of a larger store on recorded revenue and trading intensities. Floorspace

increase makes the store more attractive enabling more space for increased product ranges and to ease congestion. The increase in store size would be accompanied by modelled revenue increases, as local residents who may currently be shopping elsewhere (e.g. at the nearby town of Wadebridge, a 15 minute drive away) are likely to show an increased propensity to shop at the Padstow Tesco. The SIM reveals that a modest increase in floorspace (of 10,000 Sq Ft), resulting in a 20,000 Sq Ft store, would generate an average weekly revenue of around £300,000, rising to in excess of £500,000 during the peak-season (Table 7.1). The larger store would experience a trading intensity of around £25 per Sq Ft in the peak-season, in line with company average. However, average trading intensity would fall to around £15 per Sq Ft (below the company's reported average) but in line with a number of other stores and operators within this area. Flexible use could be made of the additional floorspace, with provision for stocking increased ranges of household goods or clothing during the low-season, enhancing facilities for residents in the town.

Table 7.1 reveals that increased floorspace provision at Padstow would have a limited impact on the nearby Tesco Wadebridge store. A modest increase in floorspace at Padstow would have an overall net-benefit on Tesco revenue derived from this area, largely reducing local residents and visitors expenditure outflow to competitors stores in Wadebridge. Figure 7.2 identifies the location of the Padstow and Wadebridge stores and demonstrates that, following investment at the Padstow store, Tesco would achieve modelled market shares of in excess of 40% in many OAs to the west and south west of Padstow and Wadebridge, representing (by floorspace) the main grocery retail provision to serve the residential and visitor populations in this catchment.
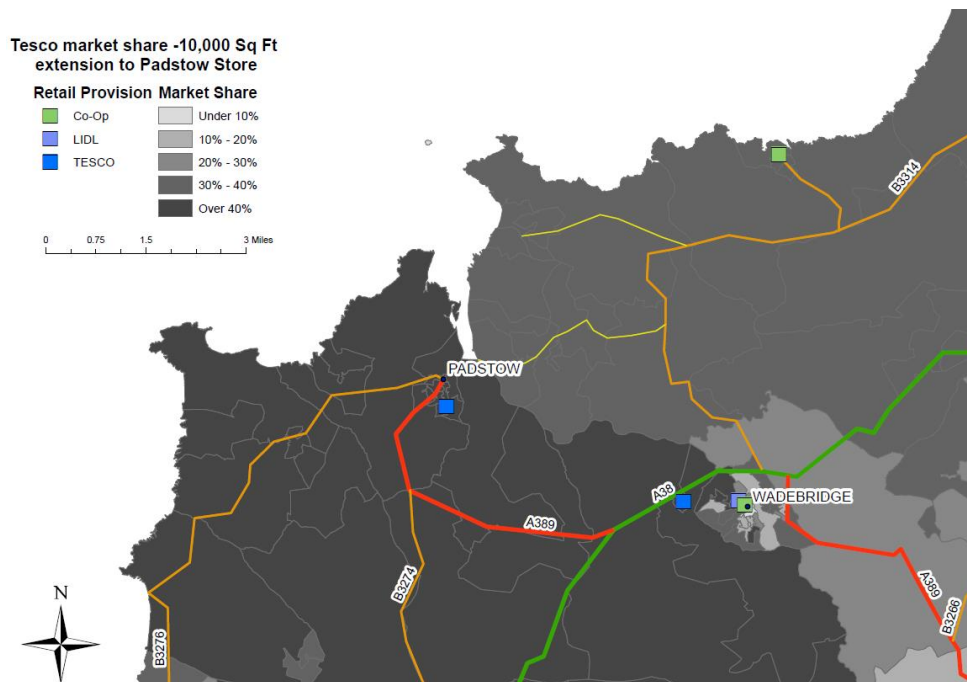
Figure 7.2 - Tesco Market Share of residential and visitor expenditure (August) following 10,000 Sq Ft extension to the Tesco Padstow store

Table 7.1 - Modelling the impact of floorspace increase at the Padstow Tesco store

	Peak Revenue	Peak Trading Intensity	52 week Average Revenue	52 week Average Trading Intensity	Impact on Wadebridge Tesco 52 week Average Revenue	Impact on Tesco 52 week Average Revenue
No Increase	£373,340	£35.56	£219,201	£20.88	£0	£0
5000 Sq Ft Increase	£452,780	£30.19	£262,004	£17.47	- £16,947	+ £25,856
10 000 Sq Ft increase	£512,677	£25.63	£299,754	£14.99	- £30,853	+ £49,700
15,000 Sq Ft increase	£561,539	£22.46	£331,473	£13.26	- £41,783	+ £70,489

This example, using an established store, outlines how the SIM can be used to identify store trading characteristics resulting from the seasonal influx of visitors, supporting both strategic and operational decision making. The model allows impacts of network interventions (such as store extensions) to be assessed, identifying their impact across multiple stores. The Padstow store has been introduced here as it exemplifies most clearly the considerable seasonal sales variations evident at some stores within Cornwall.

However, expansion of this store may not be realistically practical given its location, local planning constraints and lack of parking in this part of the resort. Rather than extend this store, Tesco have instead sought to extend their nearby Wadebridge store to meet the demand in this catchment[27]. Nonetheless, the considerable seasonal uplift and operational constraints faced by this store provide a very useful example of the model capabilities.

Having used the Tesco Padstow store to highlight the ability of the model to identify seasonal sales fluctuations, the following sections demonstrate the utility of the model for broader store location planning using two live development schemes in the resorts of Looe and Newquay. These scenarios demonstrate that the model can be used not only to estimate revenue and identify seasonal sales fluctuations, but also to evaluate the impact of store development proposals across the entire grocery retail supply side. The following scenarios provide evidence that the model can be used to inform site location planning, evaluating changes to consumer access and flows, store revenue and market shares.

7.3 Assessing proposed store developments – Looe

7.3.1 Looe

Looe is a small waterfront town and popular tourist destination located on the south coast of Cornwall, approximately 8 miles south of Liskeard. Tourism represents the town's main economic activity and much of Looe's retail provision directly caters to the needs of visitors, with a high proportion of gift and craft shops. GVA Grimley (2010, p169) note that "the role and function of the town centre is clearly orientated towards Looe's attractiveness as a tourism destination". Grocery retail provision is limited to two small Co-Op stores (one a former Somerfield), each around 2,000 Sq Ft. These stores are suitable primarily for top-up shopping, with a survey by Jackson *et al.* (2006) identifying that small-format Co-Op stores generally offer expensive and limited ranges not suitable for a weekly food shop. A handful of convenience stores complement this provision, between them serving a residential population (in the town itself) of around 5,000 along with visitors during the peak tourist season.

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[27] Planning Application PA10/03830

Looe lacks the choice or provision of retail services for residents or visitors to carry out a typical main weekly food shop. Consumers thus have to travel elsewhere for this purpose, many to the nearest large supermarket, a 25,000 Sq Ft Morrisons store in Liskeard. The Cornwall Council Planning and Regeneration Service Case Officer for a recent store development proposal in the town noted that:

> "Many permanent residents of Looe ... must currently drive to Morrisons' supermarket at Liskeard for their principal weekly food shop. Others probably visit the Bodmin or St Austell supermarkets. It is logical also to assume that thousands of self-catering holiday makers who come to these settlements and their campsites every year do likewise." (Cornwall Council, 2013b, p38). *For reference, the settlements of Looe, Liskeard, Bodmin and St Austell can be seen on the study area map (Figure* 4.1*).*

In supporting documentation for a recently proposed large foodstore to serve the town (API, 2012), developers outline the considerable benefit such a facility would offer in enabling local residents to undertake their main weekly food shop within the town, retaining expenditure currently leaking to foodstores outside the town. This section seeks to assess the extent to which additional foodstore provision in Looe would 'claw-back' expenditure from residents living within the town and its surrounding retail catchment area, reducing the dependence on stores in Liskeard for carrying out a weekly food shop. Any 'claw-back' of this form of expenditure would be likely to generate additional non-food spend in stores and services in Looe town centre, via linked trips, especially if the proposed foodstore is in an edge-of-centre location. Trade diversion from Liskeard to Looe may also detrimentally affect Liskeard town centre, which is itself facing challenges, and represents one of the 'Portas Pilot' towns and is thus subject to support and investment to help improve the viability and vitality of the town centre and its independent traders[28]

Drawing on proposed store developments to serve the town, sections 7.3.2 - 7.3.4 identify the likely impact of new foodstore provision in Looe and comment on the role of a new foodstore in:

- Retaining consumer expenditure within the town;
- Reducing distance travelled by consumers (and associated cost) to carry out their main food shop;
- Providing facilities to meet the needs of visitors to the town, including those staying overnight, visiting friends and relatives or enjoying local attractions and beaches.

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[28] See http://www.maryportas.com/portaspilots/mary-portas/

Given the importance of tourism in driving demand within the resort, this chapter also seeks to outline:

- Expected seasonal sales fluctuations within the store;
- Impacts of these variations in trading levels on operational characteristics;
- Broader impacts on the vitality and viability of Looe as a retail centre.

Section 7.3.3 also identifies the likely trade diversion from nearby foodstores and the impact of a new foodstore in Looe on grocery retailers' market shares within the former Caradon district. Section 7.3.2 begins with an exploration of current spatial patterns of consumer demand, both residential and visitor. Throughout the following sections, all market shares, demand estimation, store revenues and other values reported refer to 2010 and are derived from the modelling framework and disaggregated SIM outlined in Chapters 5 and 6, unless otherwise stated.

7.3.2   Modelling current retail provision and consumer flows in Looe

4,104 households (8,871 household residents) live within a 15 minute off-peak drive time of Looe town centre (herein termed 'Looe catchment'), with an average total weekly spend on food and drink estimated at around £266,000. Within the Looe catchment an additional £27,500 worth of food and drink expenditure is estimated to be available per week in January, rising to £312,200 per week in August. This is derived from all forms of visitor demand, including overnight visitors using commercial accommodation, induced demand by households hosting visiting friends and relatives, and day visitors to the resort of Looe and its nearby beaches. Taking 52 week average visitor demand at £125,000 along with residential demand, average weekly food and drink spend available within the Looe catchment is £390,000, rising to £578,500 during the peak visitor season (almost a 50% increase).

Figure 7.3 shows the spatial pattern of demand from local residents (52 week average) and demonstrates that residential demand is distributed fairly uniformly across the OAs that make up the study area used here, with some clusters of higher expenditure in the rural areas to the north of Looe. These are largely driven by variations in the number of households per OA rather than marked geodemographic differences, since, with the exception of Looe and Liskeard town centres, households within this area fall almost exclusively within the 'Countryside' OAC supergroup. By contrast, visitor demand (Figure 7.4) shows a higher propensity to be clustered towards the coast, with clear clusters of visitor expenditure originating from OAs adjacent to the coastline on the both east and west of Looe. To a large extent this expenditure is driven by visitors using the numerous holiday parks and camping and caravanning sites found here, with 3 large sites situated to the east of Looe on the B3253 (between them hosting over 270 static caravans/lodges and in excess of 415 touring pitches). To the west of Looe, self-catering visitors staying in over 1,500 units of accommodation face journey times in excess of 30 minutes to reach large foodstores in Liskeard or Bodmin.

Using the disaggregate SIM, modelled flows of residential food expenditure for Looe suggested that many consumers travel beyond Looe to carry out their weekly food shop, lacking appropriate choice and provision of suitable stores in Looe. Modelling reveals that the town centre Co-Op stores in Looe display a combined market share of around 27% of the OA level available expenditure within the Looe catchment, and, along with large-format Co-Op stores in Liskeard and St Blazey, the Co-Op enjoys a market share of almost 38% in this area (well above company average within Cornwall, modelled at 10.6%). The main competitor is Morrisons, operating a mid-sized store in Liskeard (around 8 miles or 20 minutes drive from Looe) and another store in Bodmin (around 30 mins drive). Morrisons has an overall market share of almost 44% of all food and drink expenditure for residents living within the Looe catchment area, over double their average market share of 19% across Cornwall.

Table 7.2 shows major retailer market share of all food and drink expenditure from residents within the Looe catchment. Figure 7.6 shows the OA level market share for Co-Op in Looe, based on modelled flows of residential expenditure (52-week average). The Co-Op (and therefore the food retail market in Looe in general) exhibits a noticeably higher market share in the OAs to the west of Looe which, given the local road network, suffer the longest journey times to larger stores in Liskeard, St Austell or Bodmin. To the north of Looe there is a clear leakage of expenditure to stores in Liskeard, facilitated by easy road access and the provision of a large Morrison's store. The OA level market shares for the Morrisons' store in Liskeard are shown on Figure 7.5. This store enjoys a large catchment with consumers travelling an average 5.53km to reach the store, which attracts almost a fifth of its revenue from the Looe catchment area.

A 2012 household survey, carried out by developers working on behalf of Tesco, (API, 2012) identified that over 50% of the main food shop expenditure originating within the Looe catchment is attracted to the Morrisons' store in Liskeard (API, 2012). The Strategic Planning Committee Report (Cornwall Council, 2013b) into the Tesco development does, however, raise some concern that the market share analysis presented by API was based on a household survey with a very limited sample size and considerable overlap with the adjacent Liskeard store catchment area. The use of a SIM, and OA level data (as opposed to postal sectors and postal areas used by the developers), suggests that these findings may partly over-exaggerate the importance of the Liskeard Morrisons, with the two Co-Op stores in Looe retaining around a third of the expenditure originating from Looe residents. Indeed, GVA (2012) suggest that 80% of top-up shopping and a small proportion of main food shop expenditure are retained in Looe. Nonetheless, given the lack of parking and limited ranges at the Co-Op stores in Looe, it is clear that additional foodstore provision is required, explored in section 7.3.3.
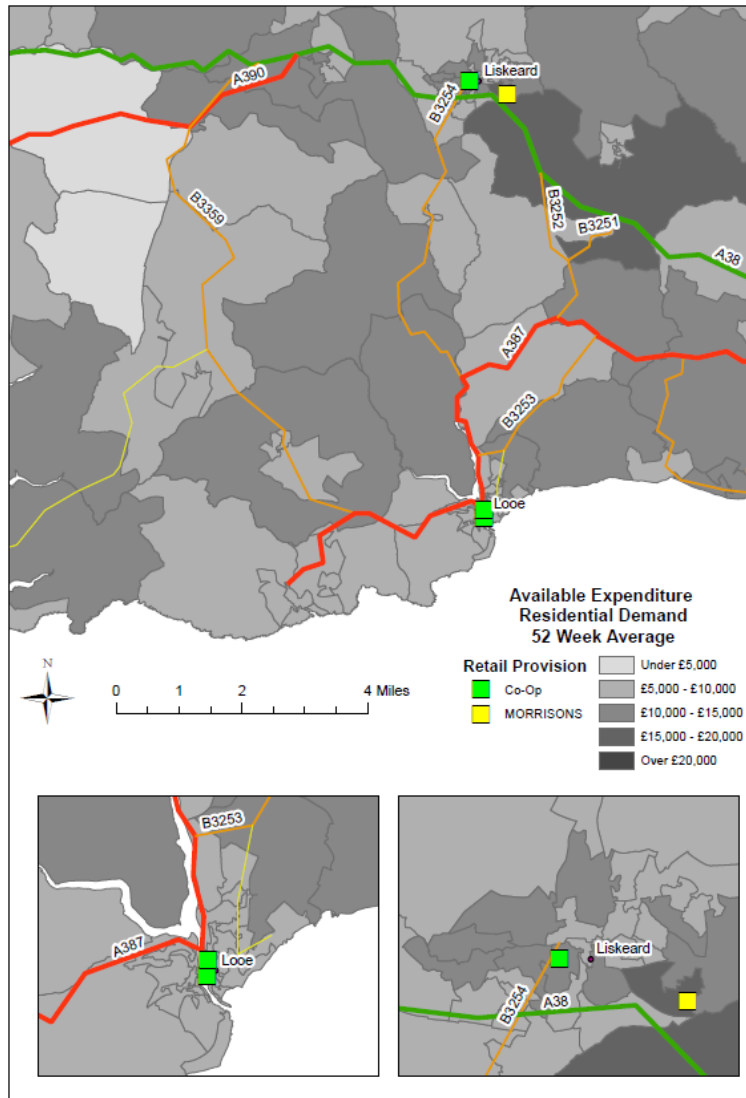
Figure 7.3 - 52 week average residential demand (2010) – Looe and Liskeard
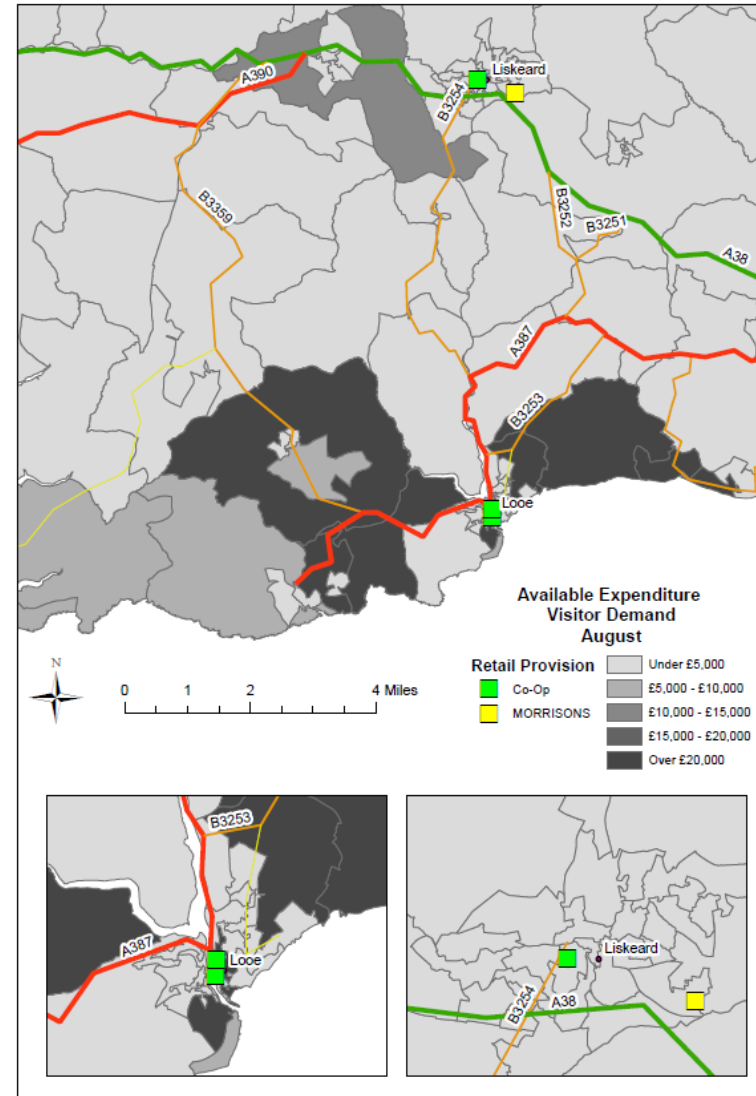
Figure 7.4 - Visitor demand in August - Looe and Liskeard

Table 7.2 - Retailers' market shares within Looe catchment (15 minute drive time) and Cornwall

Retailer	Market Share of Looe Exp. (%)	Market Share of Res Exp. in Cornwall (%)
Aldi	0.4	3.2
ASDA	2.0	9.3
Co-Op	37.1	10.6
Iceland	0.1	2.4
Lidl	3.4	6.2
M&S	1.0	3.0
Morrisons	43.7	19.0
Sainsbury's	3.1	13.4
Tesco	6.7	30.7
Waitrose	2.5	2.2

7.3.3 New Morrisons development in Looe

At the time of writing, at least three major retailers have an active interest in developing a foodstore within Looe. Tesco submitted a full planning application in February 2012 [29], which was subsequently refused by the planning committee, against the recommendation of the local planning officer(s) (Cornwall Council, 2013b). In October 2012 ASDA sought pre-application advice for a proposed store on land adjacent to the town[30]. Morrisons have also outlined their desire to open a store within Looe (Langford, 2013) and are the preferred bidder (Peacock and Smith, 2013) to develop a brownfield edge-of-centre site at Polean in West Looe. This latter proposal utilises a site which is a natural expansion of the Millpool car park serving the town centre, and is the only site specifically outlined in the former Caradon District Local Plan (Caradon District Council, 2007) as suitable for a retail/commercial or tourism development.

Based on the Tesco application, the ASDA pre-application advice and the capacity constraints of the Polean site for a future Morrison's application, retailers suggest that the town offers potential for a foodstore of around 25,000 Sq Ft. Subsequent analysis is carried

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[29] Planning application ref: PA12/06664

[30] Pre-application ref: PA12/03167/PREAPP
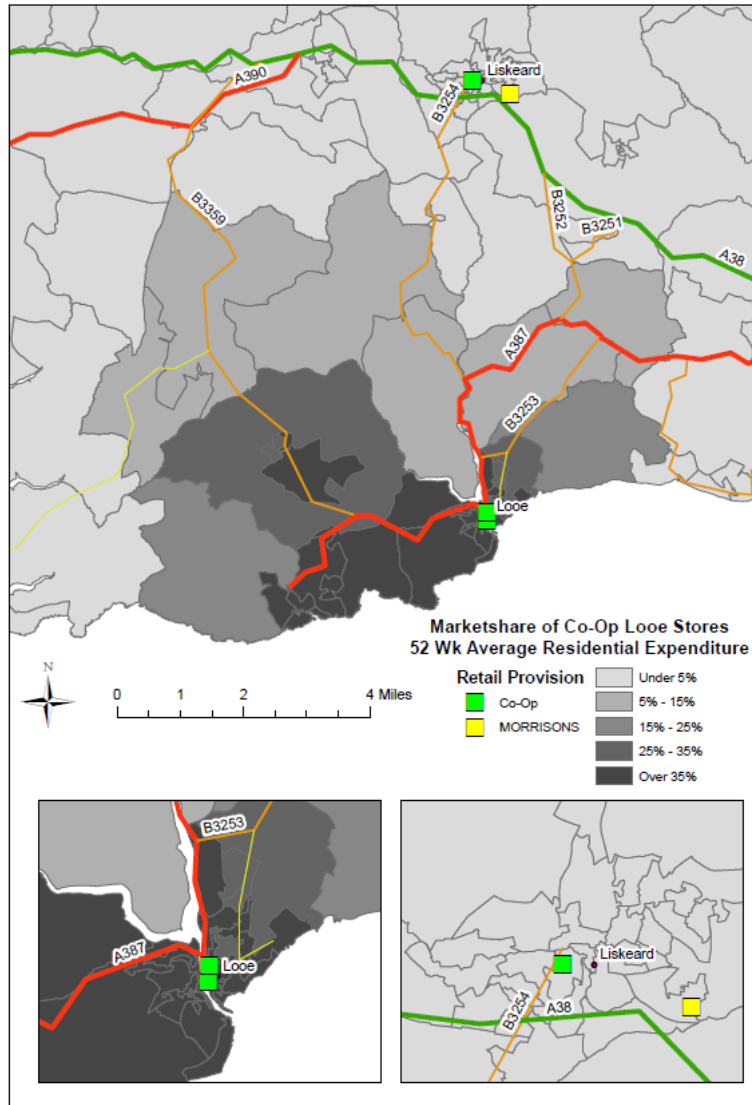
Figure 7.5 - Market share for Looe Co-Op stores
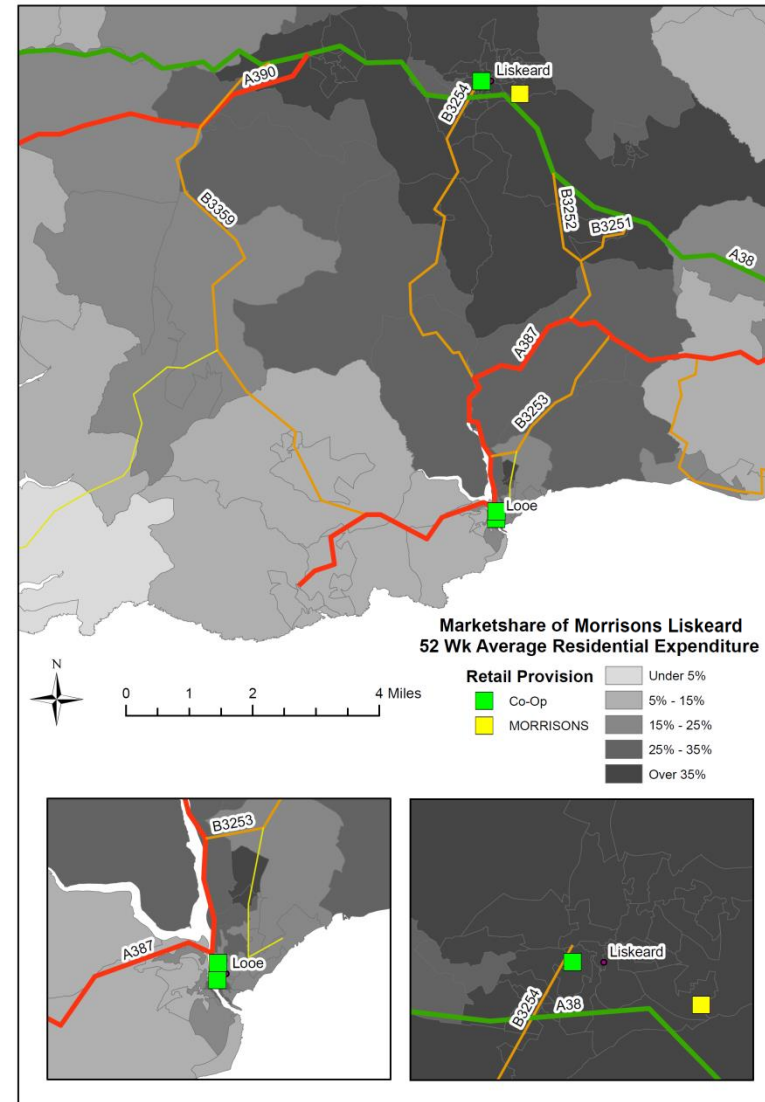
Figure 7.6 - Market share for Liskeard Morrisons store

out on a store of this size. The refused Tesco application centred on an out-of-town site to the north east of the town. The Strategic Planning Committee Report (Cornwall Council, 2013b) noted that the site favoured by Tesco was particularly convenient and accessible for visitors situated on the holiday parks to the north and east of Looe. Nonetheless, the Polean site is closer to the existing retail centre, makes use of a site earmarked for development and arguably provides better access for those residents and visitors to the west of Looe, already the most remote from foodstore provision. This section does not seek to comment on the suitability of individual sites and does not offer specific advice or recommendations based on the details of individual proposals. Rather the Polean and site is considered in conjunction with a 25,000 Sq Ft store development by Morrisons, who have demonstrated genuine commitment to opening a store in Looe. The impact of a Tesco store on the out of town Barbican Road site is also considered (section 7.3.4). This section seeks to demonstrate the considerable insight that modelling demand using the disaggregate model from Chapter 6 could offer in the preparation and assessment of new store development plans in tourist resorts such as Looe.

Taking the Polean site, a 25,000 square foot Morrisons' store has been added to the model, and, using identical parameters to those used in Chapter 6, flows of consumer expenditure to the proposed store can be evaluated. A summary of the modelling results can be seen in Table 7.3. Modelling suggests that this store would achieve average weekly revenue of around £300,000, of which around two thirds would originate from residential demand. Visitor demand is suggested to fluctuate from as little as around £15,000 per week (January) to almost £250,000 per week (August), suggesting that this store would experience considerable seasonal sales fluctuations driven by visitor demand (Figure 7.7). Based on this modelling, it is envisaged that a Morrisons' store of this size on the Polean site would trade at an average sales density of £12.23 per Sq Ft, well below the modelled company average of £17.83 for their Cornish stores. However, sales densities are identified to increase to over £18 per Sq Ft during the August peak-season. As such, a store of this size is well-placed to cope with the summer seasonal influx of visitors and any population growth within Looe, but must address operational considerations driven by a very low sales density (of less than £10 per Sq Ft) at times during the low-season, well below the usual levels experienced by grocery retailers.

In terms of the spatial pattern of trade, Figure 7.8 demonstrates that a new Morrisons' store in Looe is expected to draw its catchment from the town of Looe itself, and from the OAs to the west of Looe, where it enjoys market shares of over 50%. Very little trade is drawn from OAs to the north east of Looe, where it remains more convenient to visit stores in Liskeard. The trade area for this store corresponds closely with the distribution of peak visitor demand (Figure 7.5) and thus it is recognised that this store offers considerable benefit to both residents and visitors, especially those staying to the west of Looe. Consumer flows to this

store suggest an ATD of just over 4km, in contrast to the average distance of 5.53km travelled by residents within the catchment area prior to the inclusion of this store.

Table 7.3 - Summary of modelled store characteristics - Morrisons, Polean

25,000 Sq Ft Morrisons on edge-of-centre site, Polean, Looe			
Revenue and trading New Store (Morrisons)		**Impact on Co-Op**	
52 week Average:	£305,707	Sales (Looe)	Fell by 65.6%
Sales/Sq Ft 52-Week Average	£12.23 (£17.83)*	Market Share (Looe catchment)	Fell by 66.1%
Sales/Sq Ft January	£9.19	Market Share (countywide)	Dropped 0.5% to 10.5%
Sales/Sq Ft August	£18.04	**Impact on Morrisons**	
Average Trip Distance	4.09km (5.72km)*	Sales (Liskeard)	Fell by 11.4%
Looe catchment market share	55.8%	Market Share (Looe catchment)	Increased by 30.7%
Overall company revenue	Increased by £218,941	Market Share (countywide)	Increased 0.9% to 20.3%
* Values in brackets represent modelled company average for Cornish Stores			

Whilst offering much needed retail facilities and opportunities for linked-trips with other town centre stores and services, the proposed store will inevitably impact upon trade at other nearby grocers. In particular, the modelled impact on the existing Co-Op stores in Looe suggests these stores will face a 65.6% sales reduction (52-Week Average). Impacts would also be felt by the existing Morrisons' store in Liskeard, where 52-Week average sales are predicted to fall by 11.4% as a result of this investment. Nonetheless, with the incorporation of the proposed Morrisons' store in Looe, Morrisons' market share within the Looe catchment area increases by 30.7%, generating a net sales increase to the company of £218,941. Morrisons also have planning permission to extend their existing Liskeard store by a further 4,295 Sq Ft, although at the time of writing it is understood that this option has not yet been undertaken. Incorporating both the proposed store in Looe and the floorspace expansion in Liskeard would increase Morrisons' countywide market share by 1.2% and overall revenue derived from the Looe and Liskeard stores by a total of £265,145 (compared

to no investment). Following investment in the proposed new store at Looe and additional floorspace in Liskeard, Morrisons' expenditure inflow is modelled on Figure 7.9 and Figure 7.10, and demonstrate a good spatial fit between the existing Liskeard and proposed Looe store, with the Looe store tapping into demand from west of Looe, without impacting adversely on Liskeard store inflow from north and east of Looe.
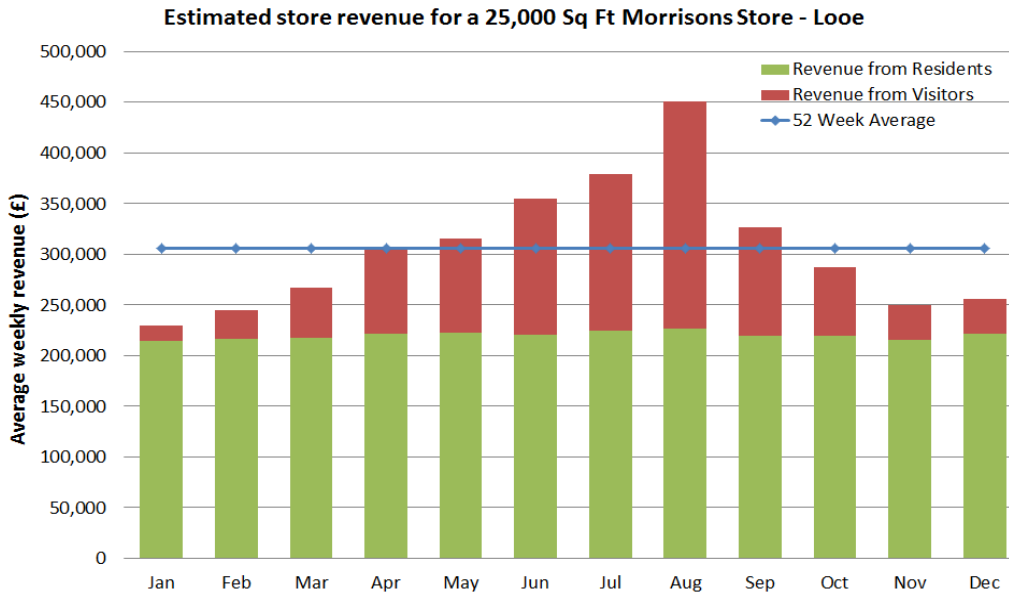
Figure 7.7- Modelled seasonal store revenue fluctuations for a new Morrisons store in Looe.
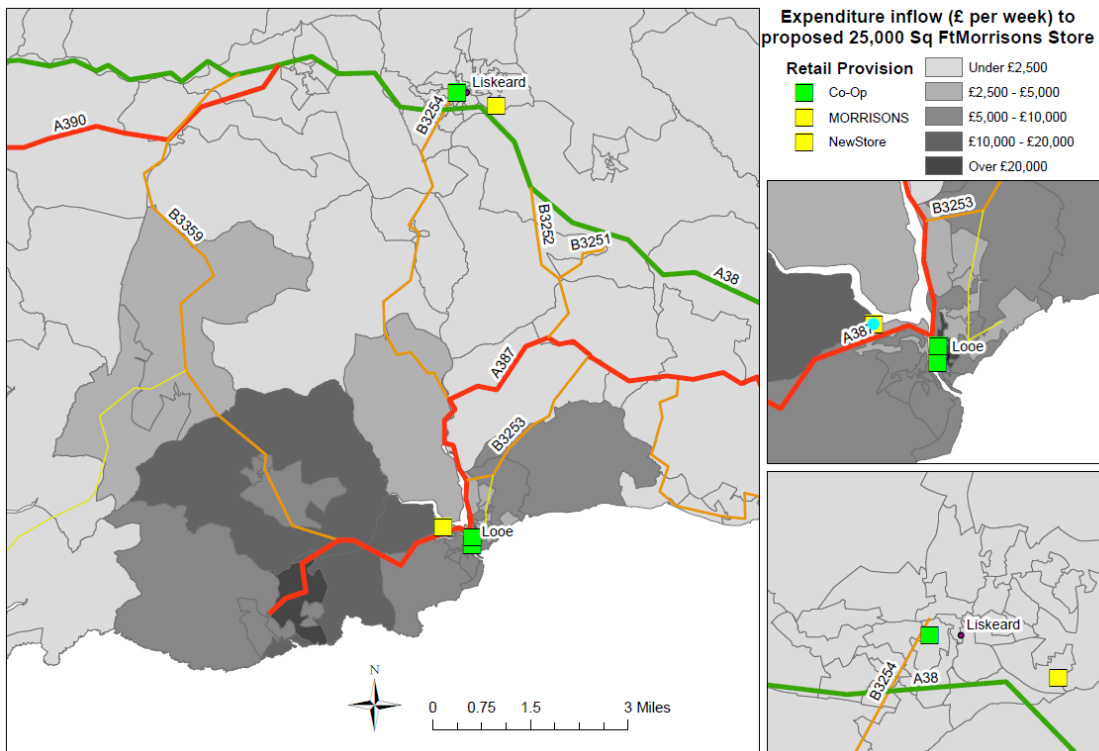
Figure 7.8 - Modelled expenditure inflow to the proposed Morrisons store in Looe.
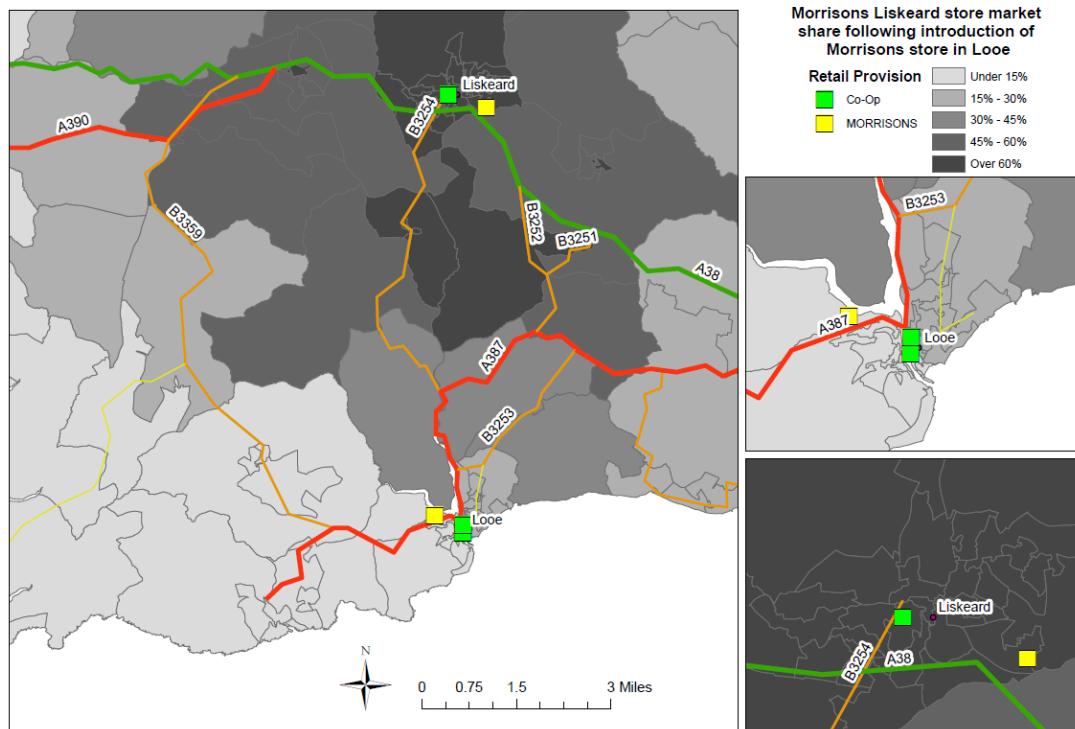
Figure 7.9 - Morrisons Liskeard Store OA level market share following new store investment in Looe

Evidence from the SIM suggests that Morrisons' interest in opening a modest sized foodstore in Looe is justified, and has the potential to increase company market share and revenue with little detrimental impact on existing Morrisons' stores. A store of the proposed size would be more than adequate at meeting the needs of both residents and visitors, and consideration would need to be given to operational issues arising from potential under-trading and excess capacity during the winter months. The potential for under-trading suggests that whilst additional foodstore provision is required in Looe, there is sufficient demand for only one retailer (a view shared by Peacock and Smith, 2013). Consequently, with Tesco and ASDA also interested in new store development in Looe, Morrisons have strongly affirmed that they will pull-out of any deal on the Polean site if any other supermarket proposal for Looe is granted planning permission (Peacock and Smith, 2013). Section 7.3.4 explores the impact of an alternative proposal based on a similar sized Tesco store development.

7.3.4 New Tesco store in Looe

Tesco have also outlined a very clear desire to open a store in the town. Although their proposal for an out-of-town store was unsuccessful, it is reasonable to assume that they would also be interested in preparing a planning application for the Polean site. Alternatively, they may seek to appeal the planning committee decision, given the local planning officer(s) recommendation for approval. The impact of the latter option, which (if granted) would result in construction of a 25,000 Sq Ft store on an out-of-town site to the north east of the town, is considered in this section.
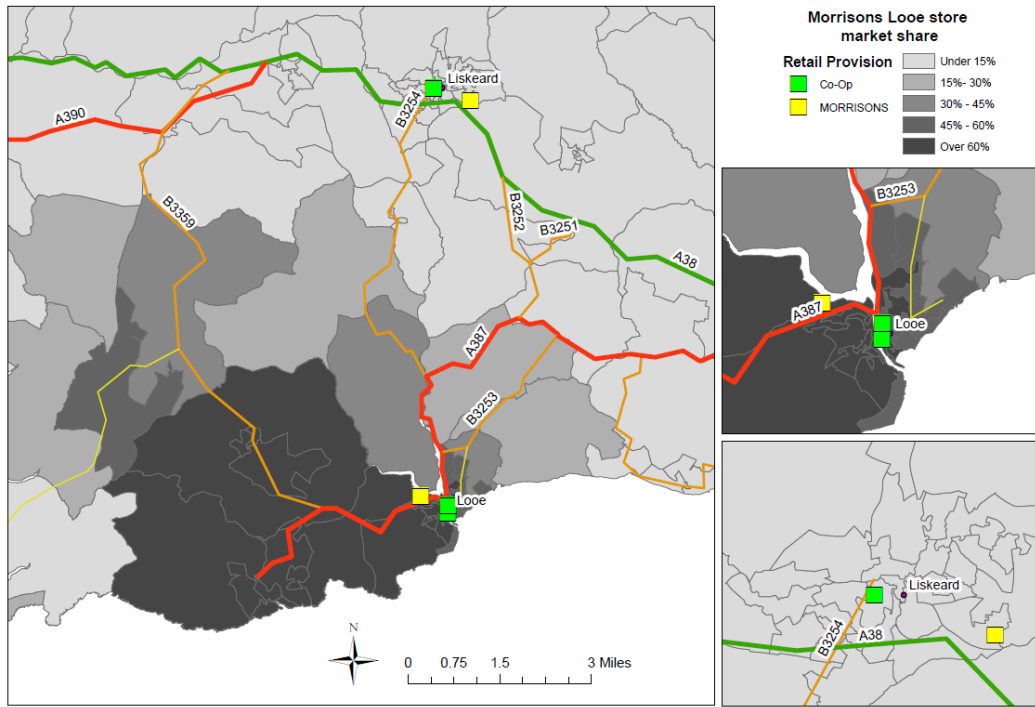
Figure 7.10 - Morrisons Looe store OA level market share

Modelled revenue predictions are based on the introduction of a 25,000 Sq Ft. Tesco store on the Barbican road out-of-town site in Looe. 52-Week average revenue for the proposed Tesco store (assuming all other supply side factors remain constant) is modelled at £351,000, comprised £266,000 residential demand and £85,000 derived from visitors (Table 7.4). In their unsuccessful planning application, developers working on behalf of Tesco asserted that this store would achieve a turnover of £17.2m pa (around £330,000 per week) (API, 2012). This incorporates a 30% expenditure uplift which they believe is driven by tourist spend, resulting in an estimated turnover of £231,000 per week from residential demand, and £99,000 per week from visitor demand. The close correspondence between modelled revenue from residential demand, and the API estimate for the trading potential of a new Tesco store, suggests that the model is operating well.

The API (2012) retail assessment suggests, however, that revenue derived from visitors remains a static 30% uplift on top of estimated residential inflow. As such, the API revenue estimates incorporate no seasonal sales variation. Modelling using visitor demand estimates and the disaggregate SIM identifies, as expected, considerable fluctuation in revenue derived from visitor demand, representing over £200,000 inflow per week in August (double the API estimate!) (Figure 7.11). As a consequence, the API estimate under-predicts store revenue by around a third, compared to the modelled revenue, during August. By contrast, API over-estimates visitor demand (by a factor of 5) and store revenue, in January.

In their critique of the API assessment, GVA Grimley (2012) note that the API sales density estimates for the proposed Tesco store (at £11.43 per Sq Ft) are well-below company average, which they believe to be around £20 per Sq Ft. Nonetheless, had the developers

incorporated fluctuations in visitor demand, overall sales per square foot would increase to £19.70 in the high-season, with the latter being more in line with company averages. The lack of agreement on the contribution of visitor demand between the modelled and API estimates highlights that the modelling approach used by the developers (using an upscale factor) cannot handle visitor demand in a robust manner.

Table 7.4 - Modelled impact of new Tesco store in Looe

25,000 Sq Ft Tesco on Barbican road out-of-town site, east Looe				
Revenue and trading **New Store (Tesco)**		**Impact on Co-Op**		
52 week Average:	£351,077	Sales (Looe)		Fell by 63.2%
Sales/Sq Ft 52 week Average	£14.01 (£15.91)*	Market Share (Looe catchment)		Fell by 65.6%
Sales/Sq Ft January	£11.09	Market Share (countywide)		Dropped 0.5% to 10.5%
Sales/Sq Ft August	£19.74	**Impact on Morrisons**		
Average trip distance	5.01km (6.25km)*	Sales (Liskeard)		Fell by 18.1%
Looe catchment Market Share	61.3%	Market Share (Looe catchment)		Fell by 60.1%
Tesco Market Share Countywide	31.9%	Market Share (countywide)		Dropped 0.7% to 18.7%
* Values in brackets represent modelled company average for Cornish Stores				

Modelled results, incorporating seasonal visitor demand, suggest that a Tesco store on the Barbican road out-of-town site would have a detrimental impact on Co-Op revenue and market share in the town, with Co-Op revenue falling by 63.2% (Table 7.4). The Liskeard Morrisons would witness an 18.1% fall in average weekly revenue and a reduction in market share, within the Looe catchment. Figure 7.12 shows the absolute difference in Morrisons Liskeard store market share of OA level expenditure after the introduction of a Tesco store in Looe. The fall in market share (and consequently revenue) is most pronounced in the OAs immediately to the east and north of Looe. These benefit from considerable expenditure

boost in the tourist season and are OAs where the Liskeard Morrisons previously enjoyed a high market share (Figure 7.5).
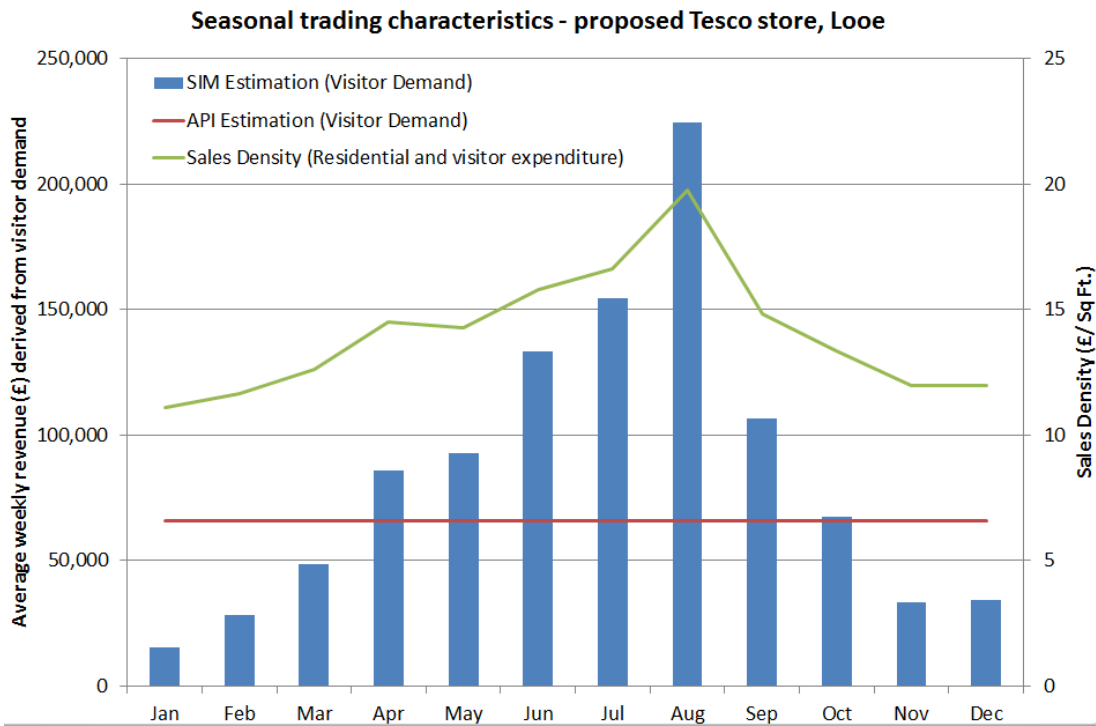
Figure 7.11 - Modelled seasonal trading characteristics of a proposed Tesco store in Looe
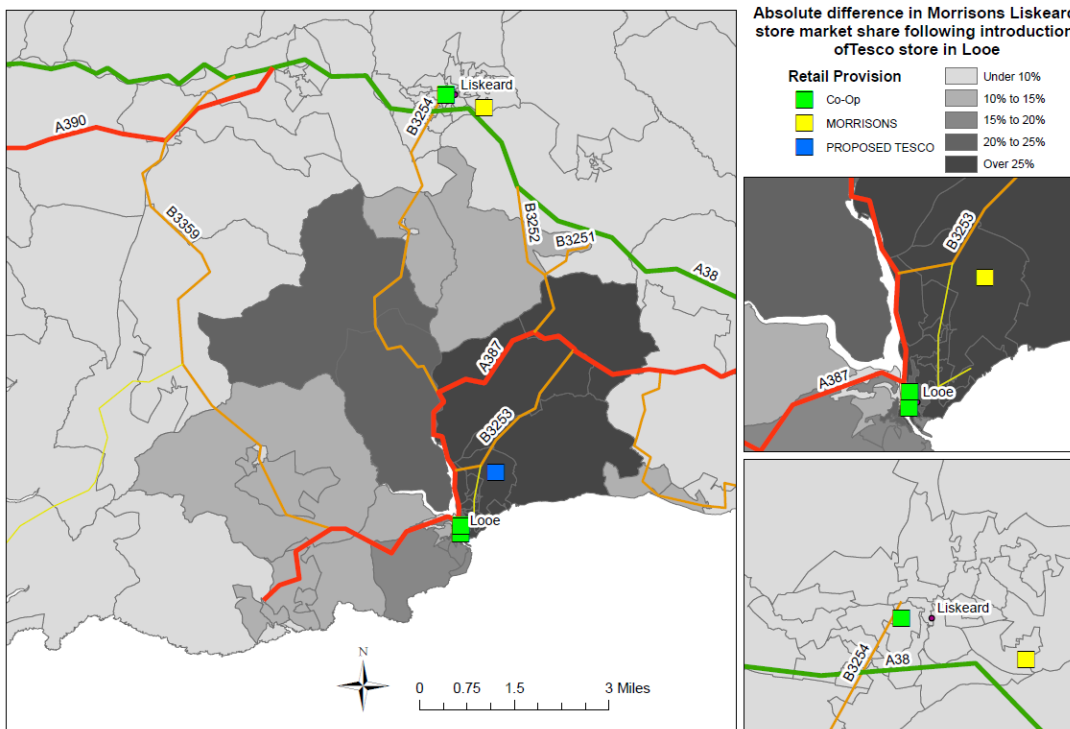
Figure 7.12 - Impact of new Tesco store development (Looe) on Morrisons market share

If Tesco were to receive planning permission for this store (or indeed an alternative deal in Looe) then the impact on Morrisons existing strong market share in this catchment would be detrimental to the company. Under this scenario it is likely that Morrisons would exercise its option to extend the Liskeard store by 4,925 Sq Ft, for which planning permission has already been obtained. This would strengthen the company's presence in the Carrick District and would negate some revenue loss. The flexibility offered by the model allows this scenario to be considered. Under this scenario, revenue would fall by just 5.1% (largely due to increased inflow from the immediate store catchment), but considerable market share would still be lost in the Looe catchment area, falling from 34.8% to 20.3%, which would be expected under this scenario.

This section has demonstrated that the SIM can be used very effectively to assess store development proposals and estimate the revenue, market shares and seasonal trading characteristics of proposed store investments in tourist areas such as Looe. It is also possible to evaluate the impact of these proposals on existing retailers, taking account of company market shares and revenues, allowing location planning teams to assess the impact of store development on their own and competitors' networks. These ideas are considered further in section 7.4, which explores the impact of a larger store development proposal within the popular tourist resort of Newquay, considering fully the implication of new store opening on existing networks and potential network rationalisation plans in response to new store development.

7.4   A new large-format foodstore for Newquay

Chapters 4 and 5 drew heavily on the characteristics of Newquay and its surrounding coastline as a popular tourist destination. Situated on the north coast of Cornwall, Newquay has grown from a small fishing village into a major tourist resort, known internationally as a surfing destination. Newquay is also a very popular resort for family holidays, especially during the August school holiday period. Continual investment in tourist facilities, services and infrastructure (including Newquay's passenger airport) seeks to ensure the resort remains a competitive tourist destination. In particular, the local plan seeks to "Maintain and enhance the stock of tourist accommodation and facilities in Newquay with an aim to provide improvements and conditions that support extension to the tourist season" (Cornwall Council, 2013a).

Current development proposals in Newquay provide an ideal opportunity to demonstrate the model's utility in a tourist resort that is larger and more complex than Padstow or Looe. Newquay has thus been chosen to form the basis of discussion in this section in order to:

- Build on the discussion surrounding Newquay and its retail and tourist provision introduced in Chapters 4 and 5.

- Explore more complex superstore development proposals, linked to larger development schemes and larger foodstore provision in out-of-town locations.
- Following new large foodstore introduction, consider network rationalisation plans by existing operators.
- Present a scenario that is of direct relevance and benefit to Sainsbury's, representing a 'live scheme' that is currently thought to be under consideration by their location planning team.

Table 7.5 - Store development proposals, Newquay

Site	1	2	3
	Site numbers correspond to the numbered development sites shown on Figure 7.13 - Figure 7.21		
Name	Quintrell Road	Trevithick Manor	Tretherras School
Applicant	Duchy of Cornwall (Owner)	Kingsley (Developer)	Tesco
Size	Up to 55,000 Sq Ft	67,200 Sq Ft	Unknown
Notes	Pre-application advice sought July 2012 as part of a broader residential and leisure developer. Retail interest unknown.	Planning application submitted 20 Sept 2012 as part of a bigger mixed use development. Clear retailer interest.	Tesco confirmed interest in this site under a controversial proposal. Planning application anticipated Sept 2013.

At the time of writing, there are at least three known proposals for new superstore development to serve Newquay (Table 7.5 and also shown on Figure 7.13 to Figure 7.21). The largest of these proposals, the Trevithick Manor development, comprises a retail park, incorporating a number of food and non-food retailers, plus other leisure facilities, restaurants and a hotel. The developers (Kingsley) have submitted a planning application[31], which includes a superstore of around 65,000 Sq Ft. Whilst the operator for the proposed supermarket is not stated within the planning documents, a spokesperson for the developer has suggested that two major superstore operators are keen to be part of the proposal (Wilkins, 2012). Local media reports and anecdotal evidence from industry contacts suggest that both Tesco and Sainsbury's are interested in this opportunity.

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[31] PA12/08909

The Duchy of Cornwall also sought pre-application advice[32] in June 2012 for a mixed use development of up to 800 homes, leisure developments and other facilities including a major food retail unit, which GVA Grimley (2013) suggest would be around 55,000 Sq Ft. It is not known whether a particular retailer is in mind for this unit, but, if successful, it is realistic to assume that it would be sought by one of the major retailers not currently represented with a large-format out-of-town presence in Newquay (i.e. Tesco, Sainsbury's or ASDA). In addition, local media reports, confirmed by both Tesco and the school itself, note that Tesco has been in discussion to purchase land suitable for a large-format store from Newquay Tretherras School on Trevenson Road.

It is clear that there is considerable interest from developers and retailers for construction of at least one large-format foodstore to serve Newquay, with a store of at least 50,000 Sq Ft, possibly larger, appearing to be feasible. Given that the Trevithick Manor development has been submitted for planning permission, and in light of the developers successful completion of similar (albeit smaller) schemes elsewhere in Cornwall (e.g. the 'West Cornwall Shopping Park' in Hayle), it is this proposal that is treated as a likely development scenario within this section.

This section seeks to:

- Evaluate current and potential spatial patterns of demand and foodstore provision.
- Evaluate retailers' current market shares within Newquay and its catchment area.
- Consider the impact of a new large-format Sainsbury's, including the impact on competitors and on Sainsbury's existing town centre store performance and potential network rationalisation.
- Consider the impact of a new large-format Tesco on Sainsbury's market shares within the town, and potential strategies by Sainsbury's to mitigate revenue and market share loss.

7.4.1 Demand and foodstore provision

Chapter 4 highlighted the importance of Newquay as a tourist destination. The provision of a considerable number of accommodation units generates a highly seasonal pattern of tourist induced grocery demand clearly evidenced via store trading figures and characteristics. Spatial patterns of residential and visitor demand are shown on Figure 7.13 and Figure 7.14 alongside an indication of the current grocery retail provision. A comparison between Figure 7.13 and Figure 7.14 clearly demonstrates the considerable demand uplift between the

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32 PA12/02206/PREAPP

low-season (January) and high-season (August), with overall demand more than doubling in many OAs, especially those to the south west of Newquay, with the coastline between Newquay and Perranporth representing a major spatial cluster of visitor demand driven by the number of holiday parks located nearby.
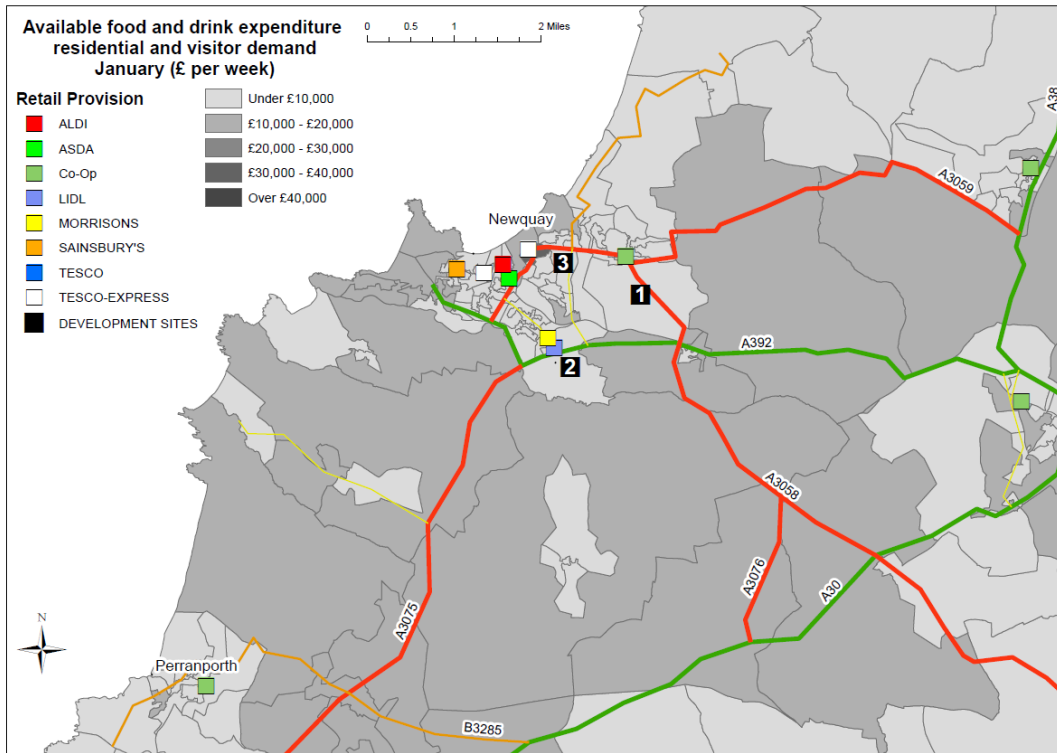
Figure 7.13 - Spatial pattern of grocery demand (January) and foodstore provision.
Site numbers correspond to the development sites shown on Table 7.5

As outlined in Chapter 4, grocery retail provision principally comprises a town centre Sainsbury's (former Somerfield) and an ASDA store (former Co-Op), alongside a very popular out-of-town Morrisons, described as an "all-embracing superstore that has a strong presence in Newquay" (Ferguson, 2013, p3). Additionally, a town centre Aldi, an out-of-town Lidl and two Tesco Express stores complement this provision, with a total floorspace of around 90,000 Sq Ft. Over half of this floorspace is concentrated within the town centre, yet Figure 7.13 and Figure 7.14 clearly demonstrate that demand is not concentrated within the resort centre, but originates more broadly from across the catchment.

Stores such as the out-of-town Morrisons and Lidl (which are immediately adjacent to the primary road network) may well be more accessible to many consumers who live or are staying near Newquay. This will be particularly true for those residents and visitors not visiting Newquay town centre, for example those living within the Newquay catchment but working in Truro, Cornwall's principal city, around a 30 minute drive from Newquay. Additionally, many visitors staying within the Newquay area may not visit the town centre itself, with strong competition from alternative resorts such as St Ives and Padstow, which offer a slightly different tourism 'product'. In particular, Newquay has been criticised as a

destination by both residents and visitors, with residents expressing frustration at the unattractive town centre environment (e.g. litter and cleanliness) (GVA Grimley, 2010), with visitors also stating concerns about parking charges (South West Tourism, 2005b).
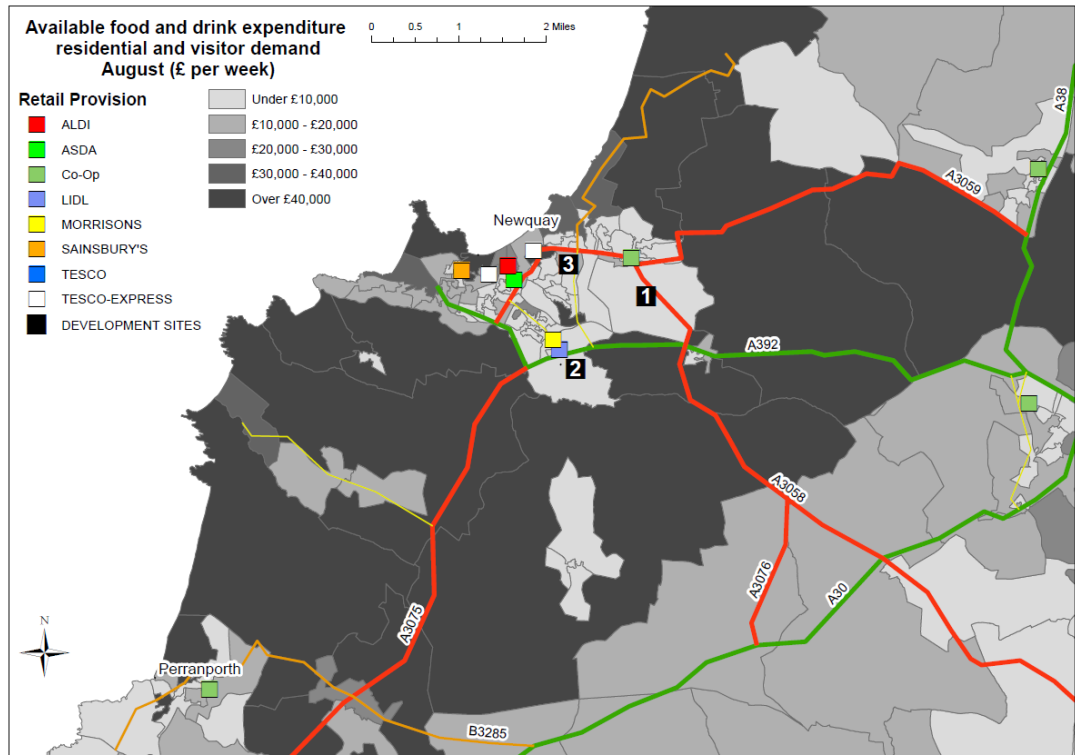
Figure 7.14 - Spatial pattern of grocery demand (August) and foodstore provision.
Site numbers correspond to the development sites shown on Table 7.5

7.4.2 Is there a need for a new foodstore?

Newquay and its surrounding catchment benefits from considerable seasonal demand uplift (contrast Figure 7.13 and Figure 7.14), which was also evidenced in Chapter 4, where the seasonal sales uplift at the Newquay Sainsbury's store was identified. The Cornwall Retail Study (CRS) (GVA Grimley, 2010) suggested that the out-of-centre Morrisons store trades above company average performance levels, supported by the SIM which identifies an average trading intensity (sales per square foot) of £20.07 at their Newquay store, compared to an average trading intensity of £17.83 across their Cornish stores. In the peak summer season, the trading intensity at this store increases to over £30 per Sq Ft per week, falling to around £14 per Sq Ft per week in January. The above-average performance of this store, particularly in the peak-season, is undoubtedly due to the important role of this store in providing a store suitable for a full weekly food shop (for both residents and visitors) coupled with easy access given its location on the A392.

Analysis of expenditure flows and subsequent store and retailer market shares also suggest that the out-of-town Morrisons store is a popular choice among consumers, especially those living or staying outside the resort centre. Figure 7.15 shows OA level market share (of 52

week average expenditure) of the Newquay Morrisons store and suggests that this store principally draws trade from the south and east of the resort, in part driven by the accessibility afforded by the A392 and A3075. This store attracts its highest market shares from the highly seasonal OAs to the west of the resort, where considerable visitor expenditure is available in the summer months.

The main town centre competition for the out-of-town Morrisons store is from the 22,000 Sq Ft Sainsbury's store, which serves a relatively limited catchment, drawn primarily from the central and eastern parts of the resort, and to some extent the coastline immediately south-east and north-west of the resort (Figure 7.16). Overall market shares are far lower than those for the Morrisons store, and the store is not able to draw trade from such a wide catchment, with very little trade originating from south of the A3075 or A392. The CRS (GVA Grimley, 2010) suggests that the town centre stores trade at more modest levels. The Sainsbury's store, for example, records an average modelled trading intensity of £10.22 per Sq Ft, compared to a company average of over £15.00 per Sq Ft in their Cornish stores (falling to around £7.46 in January). Trading at this store clearly relies on visitor expenditure, with trading intensity increasing to around £16 per Sq Ft per week in the summer peak period, still below the company's average trading intensity of just over £20 per Sq Ft per week across its entire estate (J Sainsbury Plc, 2013).
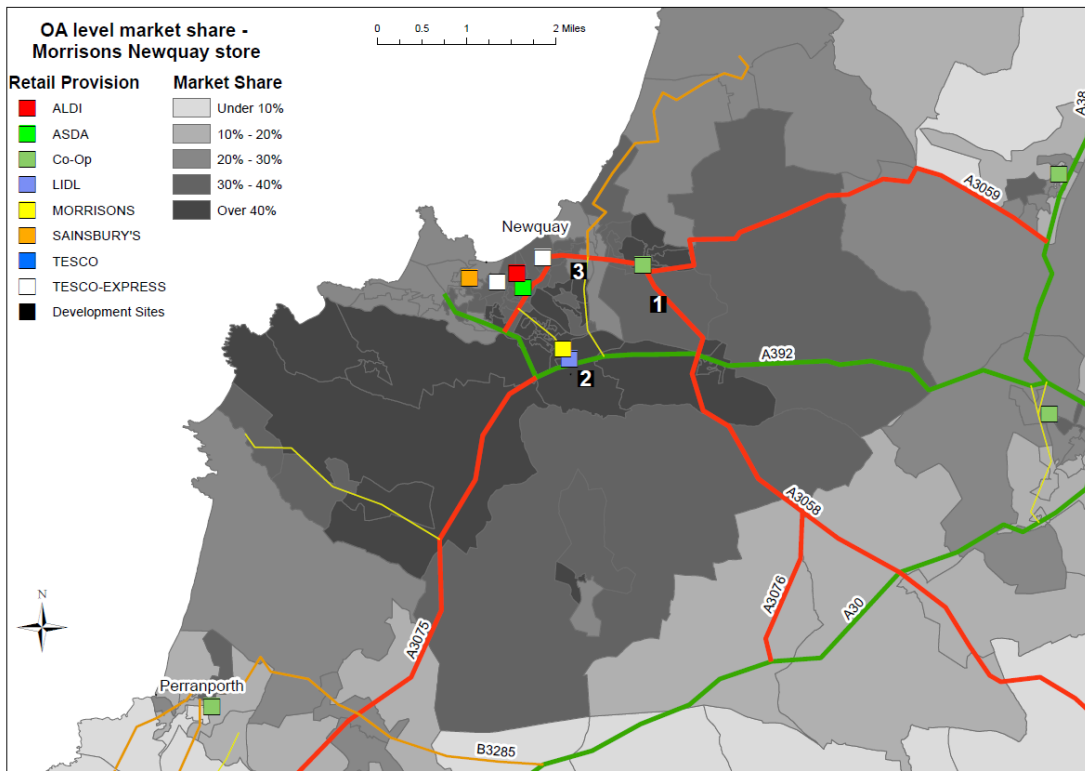
Figure 7.15 - Morrisons Market Share at the OA level - based on 52 week average visitor and residential demand

Site numbers correspond to the development sites shown on Table 7.5
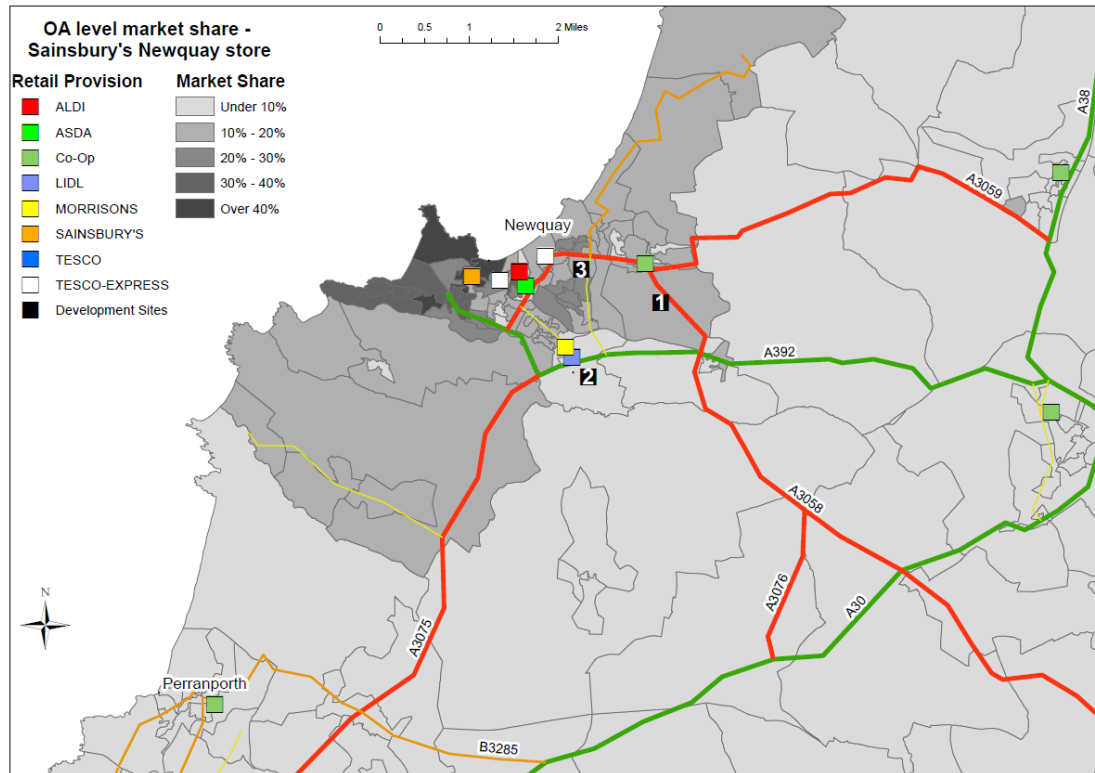
Figure 7.16 - Sainsbury's Market Share at the OA level - based on 52 week average visitor and residential demand

Site numbers correspond to the development sites shown on Table 7.5

The Hansen integral accessibility index (Hansen, 1959) can be used to identify the relative accessibility of foodstores to residents and visitors living or staying within the OAs that make up Newquay's catchment area. The index incorporates the attractiveness and distance terms from the SIM, such that relative accessibility considers both the travel 'cost' to reach foodstores, but also the relative attractiveness of those foodstores. The Hansen Index is calculated as:

$$H_i = \sum_j W_j{}^{\alpha^{kn}} exp^{(-\beta^k C_{ij})} \qquad (7.1)$$

Where: H_i represents the Hansen Index or score for demand zone i

W_j reflects the overall attractiveness of store j, whilst α^{kn} represents the additional or perceived relative attractiveness of store j for consumer type k and by store type n (often reflecting scale economies).

C_{ij} is the distance (although in this application, travel time is used) between zone i and store j, and incorporates the distance deterrence/decay parameter $exp^{-\beta}$ for household of type k.

Typical notation would use A_i to represent the Hansen index score. However, to avoid confusion with A_i used throughout the SIM as a balancing factor, H_i is used here. The A_i term used within the SIM is in fact:

$$A_i = \frac{1}{H_i} \qquad\qquad (7.2)$$

Figure 7.17 shows the Hansen Index at the OA level for the Newquay and Perranporth area, based on current foodstore provision. The actual value of H_i in each OA is unimportant in this case and is dependent on the units used for the distance and attractiveness terms. Rather, the relative difference in H_i scores between each OA is shown. Reference to Figure 7.17 reveals that those OAs to the west of Newquay experience relative inaccessibility to large foodstore provision, in spite of the considerable demand that exists within those OAs.
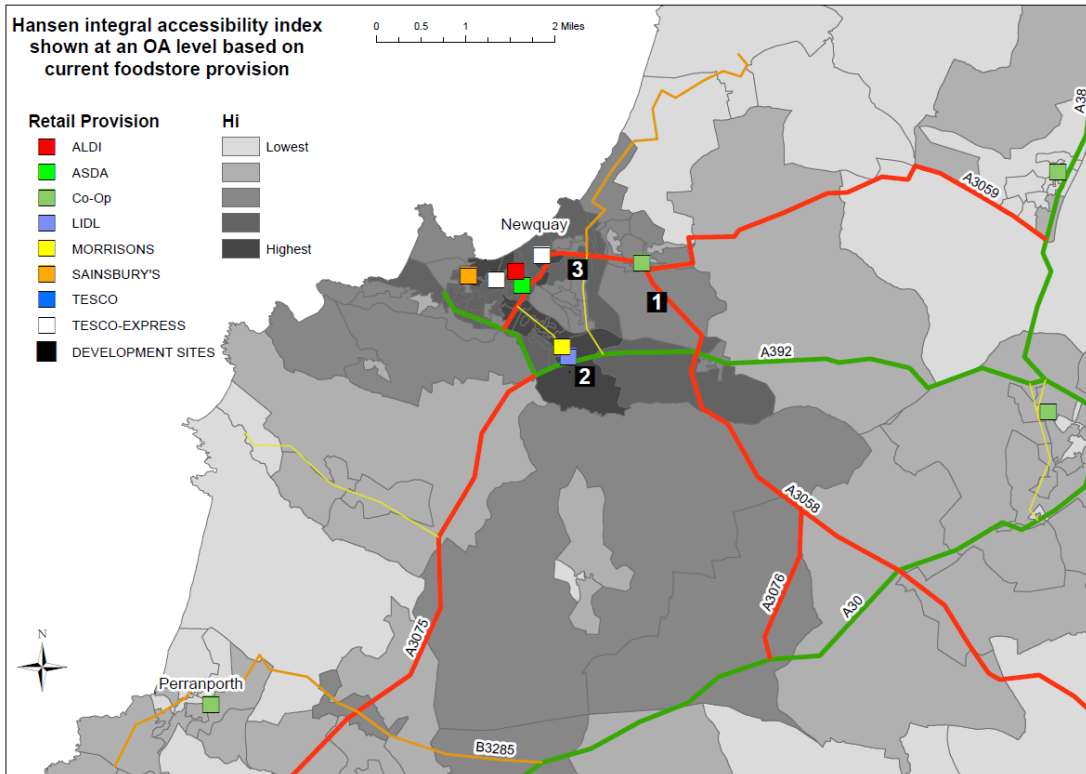
Figure 7.17 - Hansen integral accessibility index for Newquay and Perranporth based on the OA level foodstore provision

Site numbers correspond to the development sites shown on Table 7.5

Given the spatial patterns of demand shown on Figure 7.14, the current trading patterns of the two largest stores and their market shares, it appears that foodstore provision may not be geared to the needs of consumers, with consumers showing preference for the larger Morrisons out-of-centre store, which is both more accessible and offers greater choice than the town centre provision. Although the three main town centre stores (Sainsbury's, ASDA and Aldi) provide a combined floorspace of over 40,000 Sq Ft, no individual store is large enough to attract considerable consumer expenditure from the larger and more accessible Morrisons store. Additionally, concerns about the town centre environment may also have a detrimental impact on these stores trade, with considerable expenditure also leaking to stores elsewhere, particularly Truro and Redruth, both about a 30 minute drive from Newquay (the former also being a major employment and leisure destination).

The popularity of the out-of-centre Morrisons store, which has been witnessed to overtrade in the summer months and which represents the only large-format store to serve Newquay, suggests that there may be a requirement for another large-format foodstore operated by one of the major retailers, especially during periods of peak summer demand. Such a store may offer alternative consumer choice, improve access to large-format foodstores for those living outside the resort centre and claw-back some of the trade currently lost to competing centres such as Truro. Such provision could be in the form of a new out-of-town store, or via considerable improvements to the within-centre provision, such that these stores become effective competition for the out-of-centre Morrisons and competing centres.

Ferguson (2013), working on behalf of Morrisons and referring to a proposed development of an additional out-of-town foodstore to serve Newquay, states that "unequivocally there is no identifiable need for qualitative improvements to the retail offer in this location". He suggests that there is an over-concentration of out-of-centre floorspace, impacting negatively upon Newquay town centre. To some extent this may be true. However, recent development has taken place in the resort centre, driven by planning policy such as the sequential approach. The new Sainsbury's (formerly Somerfield), ASDA and Aldi stores have strengthened provision within the centre.

Following these recent foodstore developments in the town centre, the CRS (GVA Grimley, 2010) identified very little evidence of a need for additional convenience floorspace within Newquay. Even under a scenario of high population growth, they considered that there remained a need for only around 20,000 Sq Ft of additional convenience floorspace by the year 2031 (GVA Grimley, 2010). However, mapping the expenditure inflow (52 week average residential and visitor demand) to the existing Morrisons Newquay store (Figure 7.18) reveals that much of this store's trade is actually driven by inflow from the surrounding out-of-town catchment rather than from Newquay town centre itself, and in the absence of this store, modelled flows suggest that consumers would additionally shop at major stores in Truro, Redruth and Wadebridge rather than diverting all their spending to the town centre stores within the resort.

Nonetheless, modelling reveals that the out-of-town Morrisons store is the consumers' preference, and the existence of considerable demand outside of the resort centre, particularly driven by visitors, suggests that additional out-of-centre provision, easily accessible from the road network to the east and south west of the town may be needed, especially to provide consumer choice and effective competition for Morrisons.

Figure 7.19, which shows the combined market share of the town centre Sainsbury's, ASDA, Aldi and Tesco Express stores, suggests that residents living within or proximate to Newquay town centre do make use of the retail provision within the town centre. The apparent under-trading experienced at certain times of year is thus primarily driven by fluctuations in the number of visitors and the limit of residential demand available within

this catchment, and not necessarily a result of out-of-town foodstore provision. It is therefore hypothesised that any further development of town centre foodstores would be at the detriment of existing town centre provision.
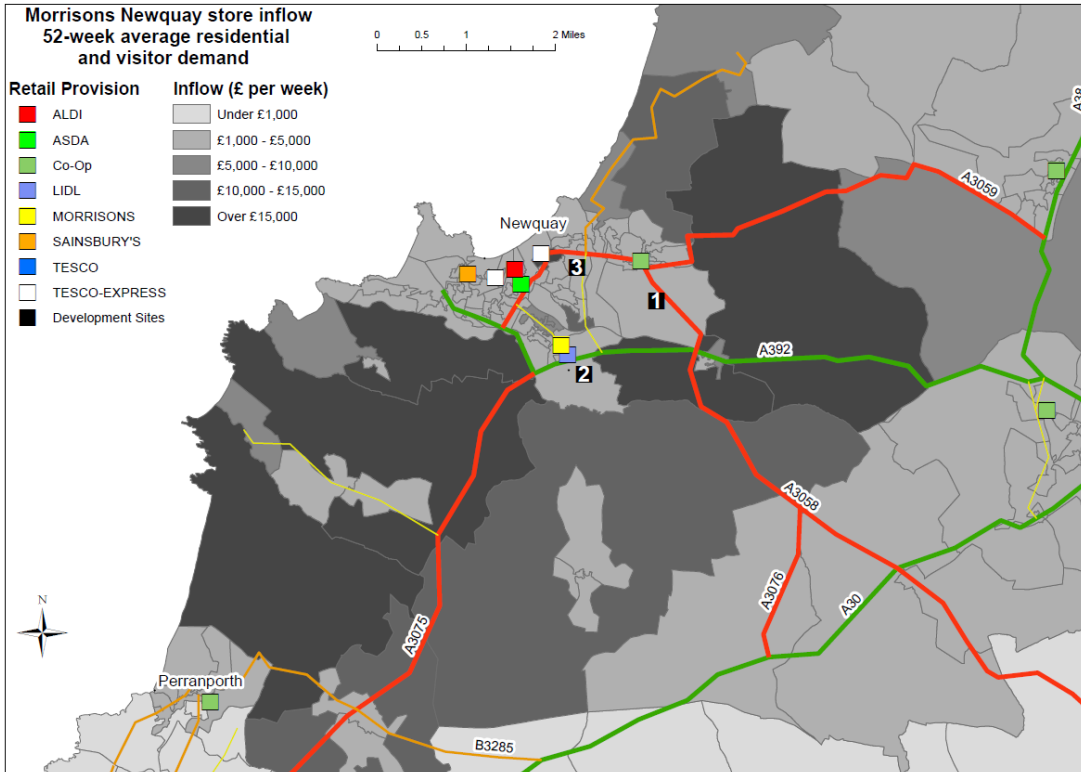
Figure 7.18 - Morrisons Newquay store inflow (52-week average based on residential and visitor demand)

Site numbers correspond to the development sites shown on Table 7.5

Given that any additional foodstore provision within the town centre would need to be big enough to compete with the out-of-town Morrisons (i.e. 40,000 Sq Ft plus), a limited range of sites are available. GVA Grimley (2013), working on behalf of Cornwall Council, identify two potential town centre sites for future large scale retail development, but note that one (Mount Wise car park) isn't large enough for a large-format supermarket and associated services, whereas land adjacent to the railway station is not currently available and would require relocation of existing services, including the town police station. Therefore, there is a lack of suitable town centre sites to enhance retail provision sufficiently within the town centre in order to compete with the out-of-town Morrisons or claw-back expenditure lost to competing centres. The Trevithick Manor site therefore may be the most suitable site that is available and realistically deliverable for new foodstore provision to serve Newquay (and this store may improve consumer choice and access to large-format foodstores).
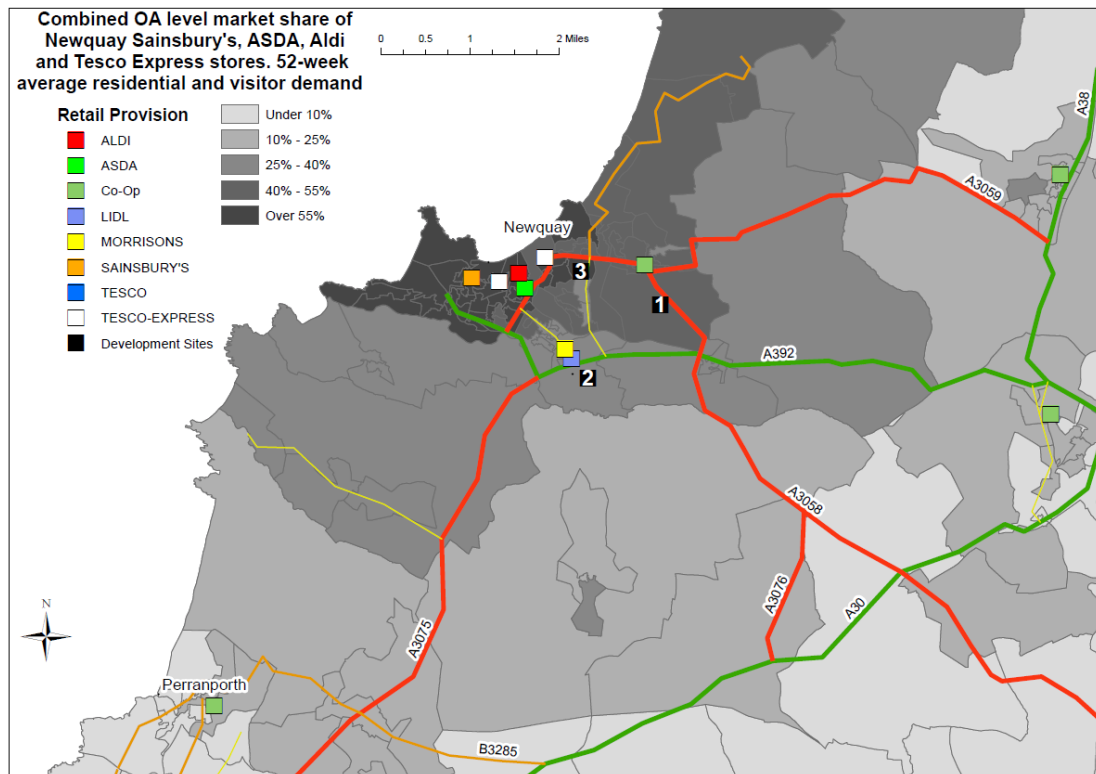
Figure 7.19 - Combined market share of Newquay town centre retailers at the OA level. 52-week average residential and visitor demand.

Site numbers correspond to the development sites shown on Table 7.5

Following store-level market share analysis and exploration of consumer flows and store-level revenue, this section concludes with the observation that:

- The town centre foodstores are found to be trading below-capacity, in spite of additional seasonal visitor expenditure influx.
- The out-of-town Morrisons is a popular and accessible store which has little competition and which is observed to overtrade within the summer.
- Major grocery retailers have demonstrated interest in opening a large-format food store to serve the town's residents and visitors.
- There is a lack of suitable sites within the town centre to accommodate a store of sufficient size to compete with Morrisons or claw-back expenditure leaking to other centres.
- The proposed large-format foodstore at the Trevithick Manor development may provide viable competition for the Morrisons store and would improve access to foodstores for the residential and visitor population to the south west of the town.

Whilst this section agrees in part with GVA Grimley's assessment that there may be limited quantitative need for a new foodstore (especially within the town centre), their assessment of need was based entirely on market share analysis (which is not able to account for potential claw-back of expenditure currently leaking to other nearby centres) and did not fully

consider seasonal expenditure inflow. Additionally, the development of an out-of-town foodstore should not be viewed in isolation, since it may be accompanied by reorganisation and rationalisation of town centre foodstore provision. These factors can all be considered fully via the use of the SIM and visitor demand estimates to evaluate the impact of new store development on the Trevithick Manor site, reported in section 7.4.3.

7.4.3 Modelling development scenarios in Newquay

This section seeks to consider the impact of three scenarios resulting from a proposed development at Trevithick Manor:

1. Sainsbury's develops a store at Trevithick Manor and maintains its town centre store.
2. Sainsbury's develops a store at Trevithick Manor and closes (or considerably downsizes) its existing town centre store.
3. Tesco develops a store at the Trevithick Manor site.

In each case, the impact on existing stores, retailers' market shares and consumer flows are identified. In all cases, the Newquay catchment refers to the area shown on Figure 7.13 - Figure 7.20, which broadly represents a 20 minute drive time from Newquay town centre. Each scenario will now be considered in turn:

7.4.3.1 Scenario 1: development of a Sainsbury's store

This scenario involves the development of a 65,000 Sq Ft Sainsbury's store at the Trevithick Manor development. Before running the SIM, Figure 7.20 first considers the impact that a new store of this size would have on local residents' and visitors' access to grocery stores. Figure 7.20 displays the Hansen Index following new store development on the Trevithick Manor site (development site 2) using identical ranges to Figure 7.17, which showed the corresponding Hansen Index scores based on current provision. Figure 7.20 shows that the introduction of this foodstore improves relative accessibility for residents and visitors in many OAs, particularly those within the town of Newquay itself and those immediately to the south of the town (connected to the proposed new store via the A3075, A392 and A3058). Nonetheless, given the lack of main access roads, those residents and visitors staying to the west of Newquay still suffer some relative inaccessibility to major foodstores, with journeys in excess of 20 minutes, although this may be inevitable given the rural nature of this part of the catchment.

Following inclusion of this store within the SIM, Table 7.6 summarises the impact of this store on trade at existing stores. The results suggest that the introduction of a large-format Sainsbury's store in this out-of-town development would provide considerable competition for the nearby Morrisons store, with sales falling by over 35%, with a corresponding fall in market share within the catchment, and a slight impact on the company's countywide performance. Accounting for seasonal variations in demand, the SIM suggests that the

introduction of a new store would divert around £11.8m per year from the existing Morrisons store, based on an average weekly diversion of over £200,000. Whilst this represents considerable sales deflection, it is far less than the £22.3m estimated by consultants working on behalf of Morrisons (Ferguson, 2013). The Morrisons store would still achieve an average sales density of £12.67 per Sq Ft, rising to almost £20 per Sq Ft in August. Whilst this is below the company average for Cornwall, it in no way "cripples" the store as suggested by Ferguson (2013), and the influx of visitor demand during the peak-season would continue to support the Morrisons store, which would maintain an important role in meeting consumers' needs.
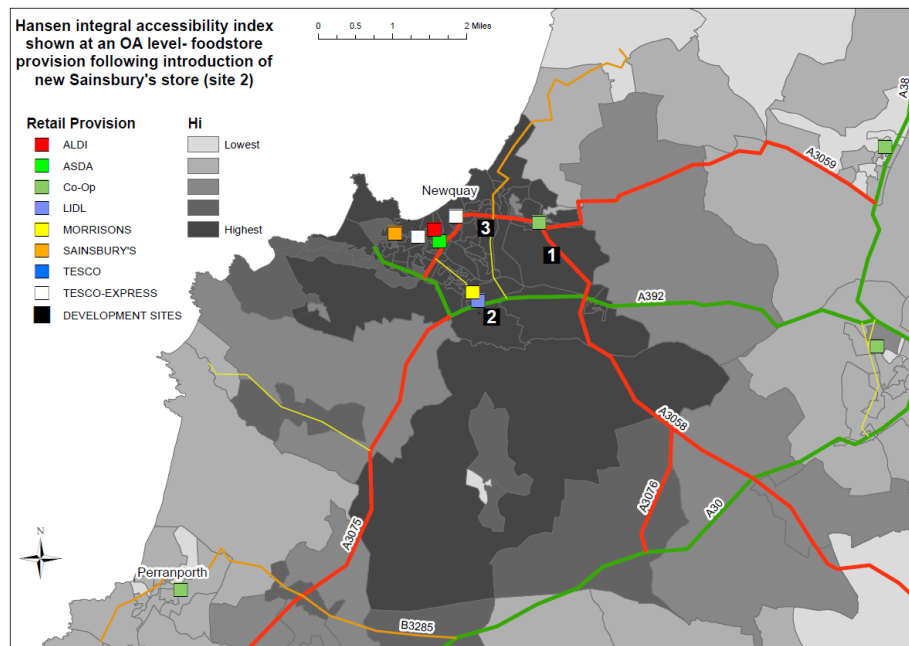
Figure 7.20 - Hansen integral accessibility index for Newquay and Perranporth

> Based on OA level foodstore provision following the introduction of a 65,000 Sq Ft Sainsbury's store at the Trevithick Manor development site (site 2). Site numbers correspond to the development sites shown on Table 7.5

Following the introduction of this store, Sainsbury's would become (by floorspace) the dominant retailer in both the town centre and out-of-town. As a result they would enjoy high market shares across the catchment area, reaching well-over 50% in many OAs (Figure 7.21). Nonetheless, whilst overall market shares and sales (across both Sainsbury's stores totalling almost £1m per week [52-week average]) would increase, the town centre Sainsbury's store would become increasingly uneconomical to run, with an average trading intensity of just £6.52 per Sq Ft per week (52 week average), falling to as low as £4.76 per Sq Ft per week in January, and never reaching more than £10.53 per Sq Ft per week, even during the peak-season. This modelling suggests that the store would fail to achieve the operating efficiencies necessary to maintain in its current format, which would need to be addressed, whether Sainsbury's or an alternative operator opened a new large-format foodstore on the Trevithick Manor site. These options are considered within scenario 2.
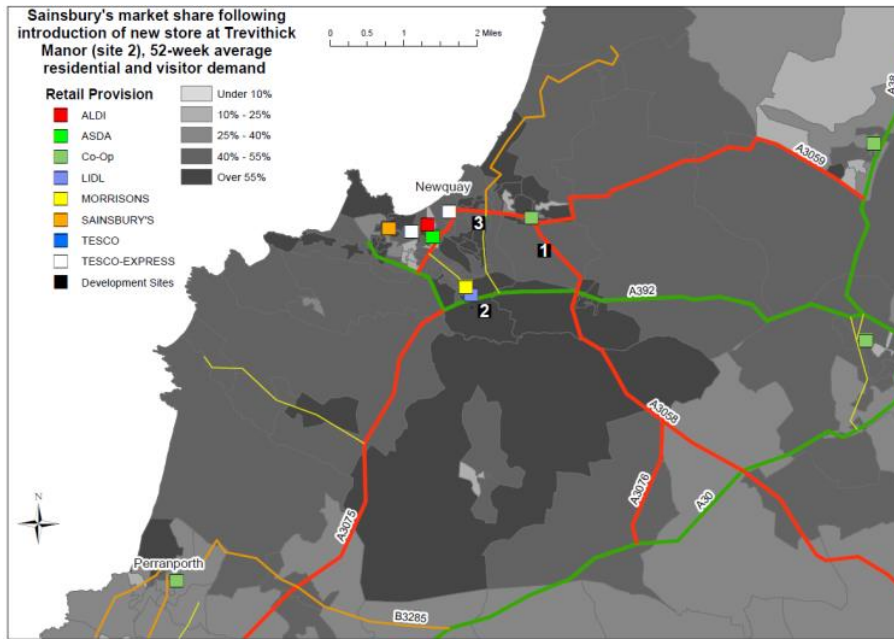
Figure 7.21 - Sainsbury's OA level market share following new store development

Site numbers correspond to the development sites shown on Table 7.5

Table 7.6 - Modelled impact of proposed Sainsbury's store at Trevithick Manor

Scenario 1: 65,000 Sq Ft Sainsbury's at Trevithick Manor			
Revenue and trading New Sainsbury's Store		**Impact on Sainsbury's town centre store**	
52 week Average:	£763,775	Sales	Down by 36.9%
Sales/Sq Ft 52 week Average	£11.75 (£14.22)*	Market Share (Newquay catchment)	Down from 18.3% to 11.1%
Sales/Sq Ft January	£526,787	**Impact on Morrisons**	
Sales/Sq Ft August	£1,227,706	Sales (Newquay store)	Fell by 37.5%
Average Trip Distance New Store	6.52km (4.84km)*	Market Share (Newquay catchment)	Down from 39.2% to 23.5%
Store market share (Newquay catchment)	38.9%	Market Share (countywide)	Fell 1% to 18.5%
* Values in brackets represent modelled company average for Cornish Stores			

7.4.3.2 Scenario 2: Sainsbury's network rationalisation

Scenario 1 clearly outlined that the introduction of a large-format retailer at the Trevithick Manor site would, all other things being equal, result in trading intensities well below average at Sainsbury's town centre store in Newquay. As a result, the company would need to consider options to maintain the viability of this store, or face store closure. Retailers are reluctant to close stores, and, since this store represented a new-investment in 2010, it is the authors opinion that the company would wish to maintain this store within the company's portfolio. This store does provide important facilities for those living and working in the town centre, and those visiting its nearby harbour and beaches. It is also considered that Sainsbury's would maintain some presence within the current store, at the very least to ensure that the store was not acquired by a competitor.

Given that Sainsbury's would need to address the under-trading that would result at this store following a new store opening at Trevithick Manor, whether by Sainsbury's or another retailer, the company would probably seek to downsize this store to operate as more of a convenience or top-up shopping function. For example, Sainsbury's operate a number of stores around 3,000 Sq Ft, offering a full range of convenience and snack foods and, if the trading area is under the 3,000 Sq Ft threshold, these stores are exempt from Sunday trading laws, enabling them to open longer hours (with these stores typically trading 7am – 11pm 7 days a week). Under this scenario, Table 7.7 suggests that the new store at Trevithick Manor would take an average of around £800,000 per week, with the revenue at the downsized town centre store falling to under £50,000 per week, though still in line with the trading patterns of some similar stores of its size. Company market share (within the Newquay catchment) would increase from 18.3% (no investment) to 45.7%, slightly less than the 50.0% anticipated if the town centre store were retained, but still a very attractive market share for a grocery retailer.

Under this scenario, overall Sainsbury's store revenue would increase over 300%, although there would be a cost involved in new store construction and in downsizing of the existing store. Nonetheless, the SIM suggests that downsizing could maintain operating efficiencies needed at the town centre store for viable operation, maintaining a clear presence for Sainsbury's within the town centre and out-of-town and retaining convenience food-shop facilities for residents and visitors to the western end of Newquay town centre. This would also accompany considerable overall growth in Sainsbury's market share and revenue derived from the catchment, with negligible impact on trading at the nearby Truro store.

Table 7.7 - Modelled impact of proposed Sainsbury's store at Trevithick Manor and subsequent network rationalisation

Scenario 2: 65,000 Sq Ft Sainsbury's at Trevithick Manor and subsequent downsizing of Sainsbury's town centre store to 3,000 Sq Ft			
Revenue and trading **New Sainsbury's Store**		**Revenue and trading** **Downsized town centre store**	
52 week Average:	£803,908	52 week Average:	£45,534
Sales/Sq Ft 52 week Average	£12.37 (£14.22)*	Sales/Sq Ft 52 week Average	£15.18 (£14.22)*
Sales/Sq Ft January	£8.53	Sales/Sq Ft January	£12.22
Sales/Sq Ft August	£19.92	Sales/Sq Ft August	£22.04
ATD New Store	6.35km (4.84km)*	ATD New Store	3.30km (4.84km)*
Store market share (Newquay catchment)	42.0%	Store market share (Newquay catchment)	3.7%
Impact on Morrisons		**Overall impact on Sainsbury's****	
Sales (Newquay store)	Decrease from £607,546 to £380,180	Company market share within Newquay catchment	Increases 27.4% to 45.7%
Market Share (Newquay catchment)	Fall from 36.6% to 24.9%	Company average weekly revenue within Newquay	Increases by £622,040 to £849,442
Market Share (countywide)	Fall 0.9% to 18.6%	Trade deflection from Truro and Bodmin stores	£32,655
* Values in brackets represent modelled company average for Cornish Stores			
** Compared to no investment			

7.4.3.3 Scenario 3: Tesco new store development

Under an alternative scenario, it is reasonable to assume that the new floorspace at Trevithick Manor could be operated by Tesco, who are rumoured to have expressed interest in that site. Under such a proposal, the impact on the existing Morrisons and Sainsbury's

stores would be very similar to that shown in scenario 1. Sainsbury's would suffer extensively, with market share in this catchment falling to just 11%, and the trading intensities that would result at the town centre store would again make this store un-economical and undoubtedly force the company to downsize. If the company were again to downsize to a 3,000 Sq Ft store, Sainsbury's overall market share in the Newquay catchment area would fall to just 3.2%, whereas Tesco would increase their market share to 43.4%, from just 4.7% before. This would be a very attractive proposition for Tesco, suggesting that it is important for Sainsbury's to try and acquire out-of-town floorspace in Newquay ahead of their major competitors.

Under a scenario where Tesco (or indeed ASDA) acquired additional floorspace at Trevithick Manor, Sainsbury's would need to consider its response carefully. Whilst downsizing of the existing town centre store is almost inevitable, the company could be creative about how to utilise the floorspace released from its town centre store (around 18,000 Sq Ft would remain after a 3,000 Sq Ft convenience store had been developed). The remaining floorspace could be operated separately as a non-food store by Sainsbury's, showcasing their growing TU range of clothing and household goods, which represent an area of strategic importance for the company. Tesco currently operate around 10 non-food stores, mainly selling household goods, whilst ASDA have also operated 11 stand-alone stores stocking their 'George' clothing range, and currently have over 10 'ASDA Living' stores within their portfolio (stocking the full range of ASDA non-food goods) (Wood *et al.*, 2010). Whilst these operators have experienced some difficulties developing these stores into a profitable format, Sainsbury's have expressed a clear commitment to expanding and promoting their non-food ranges so that the full range is available in more stores and is thus more accessible to consumers. In particular, they note that "Our non-food offer builds customer loyalty – customers who buy clothing and general merchandise, as well as food, shop with us more frequently and spend more than those who only buy food" (J Sainsbury Plc, 2013 p65). The addition of this store to the town's retail offer would maintain a strong presence for Sainsbury's in the town, enhance town centre facilities and provide viable competition for the non-food offering of the new out-of-town competitor store.

The scenarios outlined in this section have clearly highlighted that the SIM offers considerable utility in modelling consumer flows following supply side changes to the grocery retail provision within Newquay, identifying the impact on existing store and network performance and allowing a number of alternative responses, including network rationalisation, to be considered.

7.5 Conclusions

The scenarios presented throughout this chapter have made extensive use of the SIM and visitor demand estimates to assess the existing store network and new store development

proposals in Cornwall. Specifically, the popular resorts of Padstow, Looe and Newquay have been considered. The existing, highly seasonal Tesco store in Padstow, and proposed foodstores in Looe and Newquay enabled the model to be utilised and fully evaluated under a number of 'what-if?' scenarios, typical of those that would be undertaken by location planning teams. The individual nature of each resort, and the unique characteristics of demand and supply within each catchment allowed the model's versatility to be demonstrated, handling new store development and network rationalisation by Morrisons, Sainsbury's and Tesco.

The value of the model in supporting location-based decision making is clear across all three resorts. With reference to an existing highly seasonal store in Padstow, the model is able to estimate seasonal revenue fluctuations and identify the relative importance of trade originating from local residents and visitors. This has important operational implications, supporting decision making about staffing, stock levels and product ranges to meet the changing needs of the store catchment at different times of the year. The model was also utilised here to suggest the optimum size for the store, recognising that the current store over-trades during the peak season. The model was able to demonstrate that a moderate floorspace increase would generate additional sales and ease operational pressures in-store without an adverse impact on Tesco stores in neighbouring towns.

In Looe, the model has been used to simulate new store development, taking account of the proposed retail brand/fascia, allowing detailed impacts on small-area consumer flows to be considered. The model can be used to identify seasonal and spatial patterns of consumer demand, consumer expenditure flows and store/retailer market shares prior to new investment, and then, following new store investment, to evaluate:

- Overall performance and viability of a proposed new store.
- Seasonal fluctuations in store revenue, trading intensities and sales composition.
- Impact of new store development on retention/'claw-back' of consumer expenditure and the impact on consumer journeys.
- Implications for existing retailers' market shares and store revenue.

These impacts can be considered under a number of store development scenarios based on knowledge of the market and potential retailer responses. For example, section 7.3 considered impacts of store development by both Morrisons and Tesco, along with potential investment in other existing stores within the area. As such, the SIM affords tremendous potential to make multiple supply side interventions across competing retailers or centres and evaluate the impacts on consumer flows, taking full account of the impact of visitor demand, often omitted in studies of this nature.

As a larger resort with more complex retail provision and development opportunities, Newquay enabled the model to demonstrate that it can be used to generate evidence to contribute to strategic level decision making surrounding network rationalisation in tourist

resorts. Using the example of a new large-format foodstore development, the model was able to demonstrate that existing town-centre foodstore provision was under-utilised, even after taking account of visitor demand influx. Under scenarios based on either Sainsbury's or Tesco acquiring new out-of-town floorspace to serve the Newquay catchment, the model can be used to identify the impact on the existing town centre stores and to identify the impact of network rationalisation (downsizing this store) on company and competitor performance and consumer choice and access to foodstores.

In all three resorts, the modelled outputs provide a comprehensive and valuable data set that can be used as an evidence base by location planners in targeting store development or assessing the impact of competitors expansion plans. The incorporation of seasonal visitor demand clearly allows decision makers to model complex seasonal fluctuations in demand and store performance and ensure that investment is targeted towards developing store provision that meets these needs. Unlike existing approaches that are commonly employed, the modelled outputs are not reliant on any form of household survey, market share analysis, or demand up-scaling and can thus consider impacts across a whole store network, not just within one catchment, under a number of potential scenarios.

The examples used within this chapter clearly demonstrate that visitor demand estimates, used in conjunction with a custom-built disaggregate SIM, calibrated for use in Cornish coastal resorts, adds important insight to location-based decision making. These modelling tools can be used to assess a range of investment decisions, including new-store development and network-based responses to competitor store development. Chapter 8 seeks to complement these findings, developing the model for application to an alternative range of tourist resorts in Kent, where the tourism 'product', local retail network and characteristics of consumer demand present additional challenges for model-builders and location planners.

Chapter 8: Estimating and modelling seasonal grocery demand in Kent

8.1 Introduction

Chapter 5 demonstrated a methodology that can be used to estimate available grocery expenditure at a small-area level. The approach fully accounts for seasonal and spatial variations in non-residential demand driven by tourism. Seasonal expenditure inflow is driven by day visitors, overnight visitors using commercial accommodation and induced spend by hosts. Used in conjunction with a disaggregate SIM (Chapter 6), the OA level seasonal demand estimates have improved the accuracy of store-level revenue predictions in tourist areas. Using selected resorts in Cornwall, Chapter 7 presented a body of evidence which outlines that the modelling approach can be used to evaluate store and network performance within the grocery industry. With examples from Padstow, Looe and Newquay, Chapter 7 clearly demonstrated that the model can be used to evaluate supply side developments and intervention, taking full account of visitor demand within site-location assessment.

This chapter seeks to build upon the modelling and analysis undertaken thus far within this thesis, making use of an additional study area in East Kent. The introduction of an additional study area is an important step in ensuring that the modelling approach is applicable beyond the county of Cornwall, and that the approach can be applied with confidence for store location planning in alternative areas where the nature of visitor demand and grocery retail supply may be different. As such this final substantive Chapter seeks to provide wider-context to the modelling, demonstrating wider applicability of the modelling framework beyond Cornwall in order to fully meet the thesis objectives outlined in Chapter 1.

Kent, located in South East England and introduced fully in section 8.2, is a county popular with coastal tourism. The tourism 'product' exhibits a number of similarities with Cornwall, especially its seasonal nature. Kent exhibits a number of coastal resorts and in common with Cornwall these are popular destinations for highly seasonal domestic family holidays. Kent's proximity to London and the continent means that it is a popular destination for short breaks and also attracts a higher proportion of international visitors, both of which are less seasonal in nature. As such, the nature of tourism in Kent is subtly different to Cornwall and offers new challenges for modelling tourist demand for groceries. The characteristics of the tourist sector and grocery provision in the selected Kent districts are explored in section 8.2 which sets the context for this chapter and justifies the use of Kent as an additional study area to verify the predictive capacity of the SIM and associated demand side estimates.

This chapter seeks to build an understanding of seasonal grocery trade from the demand side and to use this to make inferences about the supply side. This is in contrast to the approach taken in Chapters 4 - 6, whereby an understanding of tourist demand in Cornwall was first considered on the supply side, with demand side modelling attempting to replicate the observed supply side impact of visitor spend. When building demand side estimates for Cornwall the supply side was that starting point. Before estimating grocery demand, store and loyalty card data were extensively consulted in order to understand the supply side impacts of visitor demand, and to understand the seasonal patterns of trade at the store-level. The approach taken in this chapter is the opposite; the starting point is the demand side data.

This chapter seeks to estimate the small-area seasonal grocery demand for Kent, accounting for both residential and visitor demand (Section 8.3). The approach used is very similar to the approach and methodology developed in Chapter 5, but seeks to use routinely available datasets where possible for ease of adoption by location planning teams. These estimates are used within the SIM (developed in Chapter 6) to estimate consumer expenditure flows and store revenue, calibrated against known consumer flows and store trading data (section 8.5). The Chapter concludes by considering the model's utility in simulating demand side changes such as the introduction or loss of visitor accommodation and their impact on the supply side. The purpose of this chapter is to evaluate whether it is possible for retailers to use the approach developed in Chapters 5 and 6 to construct demand side estimates which can be used to accurately estimate seasonal sales variations and store-level revenue across a range of grocery stores for which little prior information about seasonal sales fluctuations is known.

Section 8.2 begins by introducing the tourist sector in Kent, justifying the use of selected local authority districts (herein simply termed 'districts') in East Kent as an additional study area.

8.2   Contextualising East Kent as an additional study area

According to research by Tourism South East (TSE) (TSE Research, 2012), Kent attracted over 57m visitors in 2011, generating up to £3.3bn (including local multiplier effects) and supporting almost 50,000 full-time equivalent jobs. With a broad range of attractions and destinations (including coast, countryside and urban areas), Kent attracts a range of visitor and trip types. Ease of access from London and the Home Counties means that over 50% of those surveyed in a 2010 survey of visitors to Kent were identified to be day visitors from home (TSE Research, 2010), many making use of a new high speed rail link from London which has driven an increase in visitor numbers (VisitKent, 2013a). Additionally, almost 15m people passed through Kent in 2011 to reach cross-channel services at the Port of Dover and Eurotunnel (Folkestone) (VisitKent, 2012). Many of these also stop within the county

which has a well-developed network of popular attractions, including Dover Castle, the city of Canterbury and a number of established coastal resorts.

This chapter considers four districts (Canterbury, Shepway, Thanet and Dover), collectively making up East Kent and including a number of principal resorts and tourist attractions, the city of Canterbury and a large portion of the Kent coastline. The districts used have been identified on Figure 8.1, which also highlights major towns, cities and resorts alongside key transport links. The four study districts have been chosen as they encompass a range of destination types and exhibit a high proportion of self-catering accommodation for which county-wide demand is growing fuelled largely by the 'staycation' and short break market (Thomason and Keeling, 2012).

The use of East Kent as an additional study area offers a number of other benefits and opportunities. There is clear interest from Sainsbury's in understanding more about the potential to model visitor demand in this area in which they are well-represented, undergoing growth in their network and where the impact of seasonality has been noted. East Kent is an important part of Sainsbury's network. The company currently operate 8 supermarkets in East Kent, ranging from long-established stores serving town centres (e.g. Folkestone), through to recent new builds (e.g. Hythe). These stores are part of a supply of over 300 stores across the county, in which all major grocery retailers are represented. Sainsbury's have ambitious plans for store development within East Kent, with an 80,000 Sq Ft store recently granted planning permission to serve the towns of Margate, Broadstairs and Ramsgate (collectively referred to as Thanet) (as a replacement for an existing store), and at least two other new store developments or existing store refurbishment proposals evident within local media and submitted planning applications.

Whilst the impact of seasonality on Sainsbury's store trading characteristics has been noted (Feltham and Davis, 2010), seasonal peaks in tourism and the corresponding degree of seasonal sales uplift (at a store-level) are far less pronounced compared with Cornwall. Chapter 4 illustrated that stores in the Cornish coastal resorts of Bude and Newquay experienced considerable seasonal sales uplift during the peak tourist season, with store-level sales as much as tripling during the peak summer season. By contrast, analysis of store sales data for the eight Sainsbury's stores in East Kent suggests that only stores in Deal, Hythe and New Romney experience any noticeable seasonal sales uplift during the peak season, with the sales uplift representing at most a 20% increase on corresponding low season sales. It is thus interesting to explore the potential of the SIM and demand side estimates of visitor grocery spend in a series of destinations within East Kent where overall demand uplift may be less pronounced, but where this form of expenditure still contributes a proportion of store revenue and must be accounted for to accurately predict store revenue in advance of new store investment.
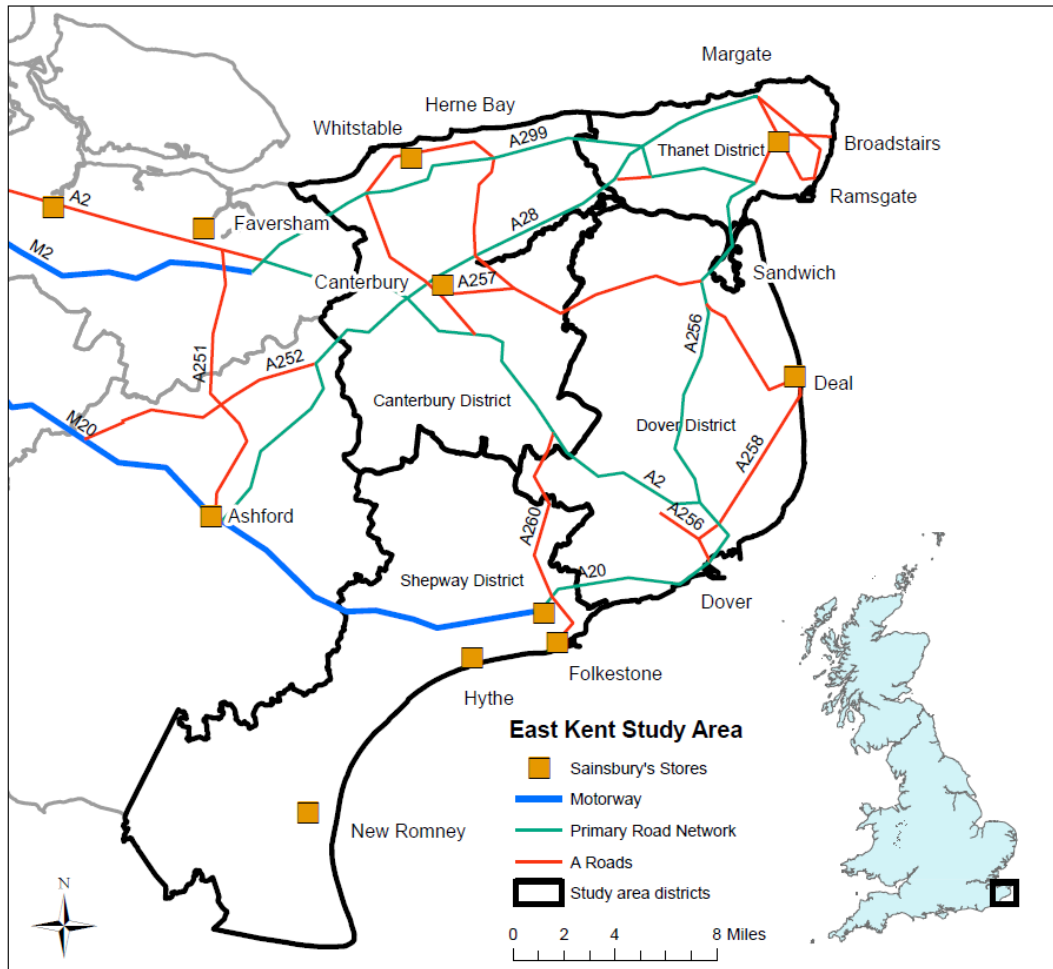
Figure 8.1 - East Kent study area

There is also an interest and commitment on the part of the local tourist organisation (VisitKent), who are interested in understanding more about visitor demand and consumption of groceries, particularly where they can inform local campaigns such as 'Kent Breakfast[33] which aims to encourage local accommodation operators to supply and promote local produce through the breakfasts they provide guests. Kent benefits from a well-developed range of data and local surveys on tourism, much of which is reported at the district level. VisitKent has been willing to provide existing high quality data, and to commission a bespoke survey for this research (see section 8.3.1.2) through their well-established network of accommodation operators. As part of the EU funded SusTRIP (Sustainable Tourism Research and Intelligence Partnership) programme[34], VisitKent has developed detailed local data collection for the benefit of the industry as a whole. This includes insight on traditionally under-researched sectors, such as VFR tourism, where findings from a comprehensive local survey undertaken in Kent were discussed in Chapter 3.

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[33] See for example: http://www.producedinkent.co.uk/KentBreakfast.shtml

[34] http://www.sustainabletourismresearch.eu/index/home

Visit Kent also has an excellent relationship with many tourist businesses in Kent, including over 300 attractions, accommodation and transport operators who feed into a monthly 'business barometer' and provide timely feedback on the performance of the whole sector county-wide. This can be coupled with detailed data from the Cambridge Model, which, as introduced in Chapters 3 and 5, is an important tool for evaluating the economic impact of tourism at the local level. VisitKent commissioned analysis from the Cambridge Model in 2003, 2006, 2009 and 2011. Considerable local level data input is required, especially where district level analysis is reported, and, by frequently commissioning such analysis, Visit Kent has a well-developed infrastructure for local data collection to operationalize the model. Results from the Cambridge Model are available at the district level, and in generating their expenditure and impact estimates, different rates have been applied on a district by district basis, making full use of local data. This is in contrast to Cornwall where countywide rates had been used, and means that estimates of the volume and value of tourism in individual districts can be drawn from the results for use in this study.

Kent offers an obvious additional study area in order to develop and evaluate the performance of demand side estimates and the SIM in a different context. The nature of the tourist industry and supply side in Kent is sufficiently similar to Cornwall that it should be possible to apply the approach used in Cornwall. Nevertheless, the relative importance of certain forms of tourism (such as VFR and day visitors) in Kent provides a challenge and opportunity to develop the model. The first half of this chapter (sections 8.3 and 8.4) seeks to develop seasonal demand side estimates of grocery spend, drawing on the methodology presented in Chapter 5. The Chapter then uses these estimates in conjunction with the SIM and evaluates the model's performance at replicating observed flows and in handling demand side scenarios (Sections 8.5 and 8.6).

2011 has been chosen as the study year. It coincides with census data, store-level data provided by Sainsbury's, tourism data supplied by Visit Kent, and is the base year for the Cambridge Model outputs for Kent. It should be noted that a late Easter, coupled with an extra bank holiday for the Royal Wedding (April 2011) may have influenced holiday making behaviour around Easter, and as such, indicators of the tourist industry (such as occupancy rates) or the supply side (e.g. recorded sales uplift) may not be representative of usual characteristics at this time of year. Additionally, within the study area, the opening of a major new art gallery, and large scale regeneration of tourist infrastructure in Margate during April, plus a major golfing tournament held in the town of Sandwich in July, may also have skewed occupancy figures and recorded store sales locally as a result of these events.

In common with Chapter 5, expenditure estimates require detailed information on the accommodation stock and its associated seasonal occupancy or utilisation, to which expenditure rates can be applied. In order to estimate seasonal demand, both visitor and residential demand are considered. The approach used to estimate residential demand is very

briefly considered in section 8.4 and uses an identical approach to Chapter 5. The development of residential demand estimates for East Kent is not discussed in any detail since the primary concern with this chapter is to demonstrate that visitor demand can be estimated, using the methodology developed within this thesis. In common with Chapter 5, expenditure associated with commercial and non-commercial (second home and VFR) visitor accommodation is considered, alongside day visitor and host spend. Section 8.3 develops small-area visitor expenditure estimates, beginning with expenditure associated with visitors using commercial accommodation.

8.3 Small-area seasonal visitor expenditure estimation

In common with Chapter 5, visitor expenditure estimation incorporates a mix of 'bottom-up' and 'top-down' approaches, building up at the OA level from the available accommodation stock (where available). Such an approach takes the accommodation stock as the 'building-block', applying surveyed visitor utilisation and expenditure rates. Where sufficient data does not exist at the OA level a top-down approach is used, disaggregating district level estimates of visitor numbers or associated spend across the study area, taking account of the likely seasonal and spatial distribution. An overview of the approach is provided within the commentary in this section, though a full outline and justification of the approach used is presented in Chapter 5 and not repeated here. Rather, the discussion seeks to focus on the use of (where possible) readily available data such that the approach could feasibly be applied by a retail location planning team for use in store-location planning. Each form of expenditure attributable to visitors is considered in turn, beginning with commercial accommodation. Accommodation provision is first outlined, before considering utilisation and expenditure rates. Section 8.4 uses these estimates to outline seasonal and spatial patterns of grocery demand in East Kent.

8.3.1 Commercial accommodation

8.3.1.1 Accommodation provision

Data relating to the commercial accommodation were supplied by the research team at 'VisitKent', the organisation responsible for tourism marketing, research and development for the county. As outlined in section 8.2, the research team have benefitted from a recent EU funded project (SusTRIP) which has made provision for local data collection. Three accommodation audits were completed as part of SusTRIP and have been made available for this study comprising:

a) Serviced Accommodation – database as at June 2011;

b) Self-catered accommodation – database as at December 2011;

c) Camping and Caravanning – database as at December 2011.

The accommodation audits have been completed in a number of stages which included an initial audit (undertaken by VisitKent) followed by considerable effort on the part of external consultants to incorporate additional accommodation information held by district councils and updates based on web searches, brochures and contact with accommodation agencies (verified by telephone contact with operators and owners where discrepancies arose) (Thomason and Keeling, 2012). The database lists individual 'properties' and associated attributes. A property may be a holiday park, individual accommodation unit (in the case of rented cottages/apartments) or a hotel/B&B etc. In all cases, further attribute information is provided, such as the number of individual units available for hire, the number of camping/touring pitches on a holiday park or the months of operation.

In common with the data used for Cornwall (Chapter 5), it is inevitable that there will be some errors or omissions within these accommodation audits. In particular, entry and exit to the sector is easy and accommodation provision, capacity and operating seasons can change frequently (Johns and Lynch, 2007). In Chapter 5 considerable additional effort was taken in order to update, verify and 'clean up' the accommodation database provided by the equivalent organisation covering Cornwall. The accommodation database provided by VisitKent has been completed by specialists with access to the most comprehensive information on accommodation supply. Retailers (or any other service providers interested in similar analysis) lack the resources to verify, validate or update the accommodation audit for anything but the smallest of areas, and, with the exception of the largest sites, the omission or introduction of individual units or small sites has a negligible impact on overall expenditure estimates. Since this research aims to demonstrate the potential of this form of modelling for use within the retail sector, the decision has been taken to undertake very little further verification or updating of the accommodation audit provided by VisitKent since retail location planning teams lack such resources and would need to use such information in an off-the-shelf format.

The database was, however, given inspection and clean-up which involved adding missing postcodes, assigning properties or sites to districts (where this information was missing) and verifying that rented cottages/apartments have been allocated to their location rather than the registered address of an agency. Countywide, there are just over 1,000 self-catering cottages and apartments available, over 6,500 camping and caravanning pitches plus over 12,000 static caravans and similar lodge style accommodation, primarily located on holiday parks. Around 20% of the self-catering accommodation stock is available all year round, whereas the remainder operate seasonally (generally March to November). Additionally, serviced accommodation provides over 18,500 bedspaces, of which over 40% are within the East Kent study districts, predominantly within small establishments, with an average room count of just 19 per establishment.

The study districts represent over 50% of the countywide accommodation stock (Table 8.1). Provision within these districts is split across a range of unit types, providing a variety of accommodation options. The dominance of static caravans and similar lodge style accommodation is clear, with the former representing a considerable proportion of the accommodation stock in certain resorts (e.g. New Romney and Herne Bay) generating spatial clusters of visitor demand which are considered in section 8.6.

Table 8.1 - Accommodation supply by Local Authority District - East Kent

Local Authority District	*Camping and Caravanning pitches*	*Self-catering cottage, apartment or lodge*	*Static caravans and lodges*	*Serviced establishment*
Canterbury	877	350	1,916	128
Dover	753	333	1,152	79
Shepway	1,272	61	1,279	57
Thanet	450	40	2,452	82
Total	**3,352**	**784**	**6,799**	**346**

Around 30% of the self-catering cottage stock is managed by an agency, with a total of 24 agencies advertising properties in East Kent. The largest are Freedom Holiday Homes (116 units countywide) and Cottages4You (101 units countywide). Within the database, the largest operators have individual postcodes identified for each property, such that they can be distributed across the study area based on the actual property locations. By contrast, for some of the other operators, properties appear to have been grouped by location within the accommodation audit and given an generic postcode based on the town/village in which they are located. For example 'Curlew Cottages' have 16 units in the Broadstairs area and all have been allocated the same postcode (CT10 1LU), representing a point close to the centre of the resort. Closer inspection of their website reveals that these properties are actually distributed around the town/resort. Since this chapter seeks to apply routinely available 'off-the-shelf' data these properties have not been reallocated to their actual locations (which would be an almost impossible task without local knowledge and detailed reference to the property descriptions and accompanying photos on the agencies website). Nonetheless, all agency units do appear to have been assigned, at the very least, to a suitable postcode within the resort where they are located. This is considered to represent an acceptable level of accuracy for investigations of this nature since the re-allocation of individual accommodation units and their corresponding demand within any individual resort will have negligible impact on spatial patterns of demand or store-level revenue.

The spatial distribution of the accommodation stock is shown in Figure 8.2 for the East Kent study area. In common with Cornwall (Chapter 5), serviced accommodation clusters predominantly towards urban areas, with clear concentrations of this form of accommodation within Canterbury, Dover and the Thanet coast. This is unsurprising, with Canterbury representing a major destination for visitors to East Kent. Dover and Folkestone exhibit a high provision of budget chain hotels (e.g Premier Inn), providing accommodation for cross-channel travellers. Figure 8.2(b) outlines the spatial distribution of all forms of self-catering accommodation (in terms of bedspace provision), incorporating camping and caravanning at the LSOA level across the study area. There is clear evidence of spatial clustering, especially along the Shepway coast, taking in the resorts of New Romney and Hythe, between Dover and Deal and along the North Kent coast between Margate and Whitstable.

In common with Cornwall, it is likely that the tendency exhibited for self-catering accommodation to cluster around particular resorts and destinations is likely to lead to spatial clusters of visitor grocery demand during the peak season, as explored through the application of expenditure and occupancy rates in section 8.3.1.2.

8.3.1.2 Accommodation occupancy, utilisation and expenditure

In common with Chapter 5, grocery expenditure associated with visitors using commercial accommodation is calculated by taking account of seasonal occupancy or utilisation rates in conjunction with expenditure estimates, applied once again on a per-unit and per-week basis. VisitKent benefit from a recruited network of accommodation providers who supply occupancy data on a monthly basis using an online system known as RIBOS[35] (ReZolve Internet-Based Occupancy Software), a commercial system which VisitKent subscribe to, and which feeds into the serviced accommodation occupancy survey carried out by VisitEngland. RIBOS benefits from high participation as businesses are able to easily benchmark their performance against others and cash prizes are provided to encourage accommodation providers to take part. On a monthly basis, occupancy rates (room) are available for all forms of serviced accommodation, individually for B&B, guest house and small hotel/inn, and also by location (seaside, large town/city, small town, and countryside/village).

It is important to use these local rates, since occupancy rates for guest house and B&B accommodation in Kent has been reported to show a tendency to be above the national average (Tourism in Kent, 2011). The occupancy rates applied are shown in Table 8.2.

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[35] http://eos.ribos.co.uk/
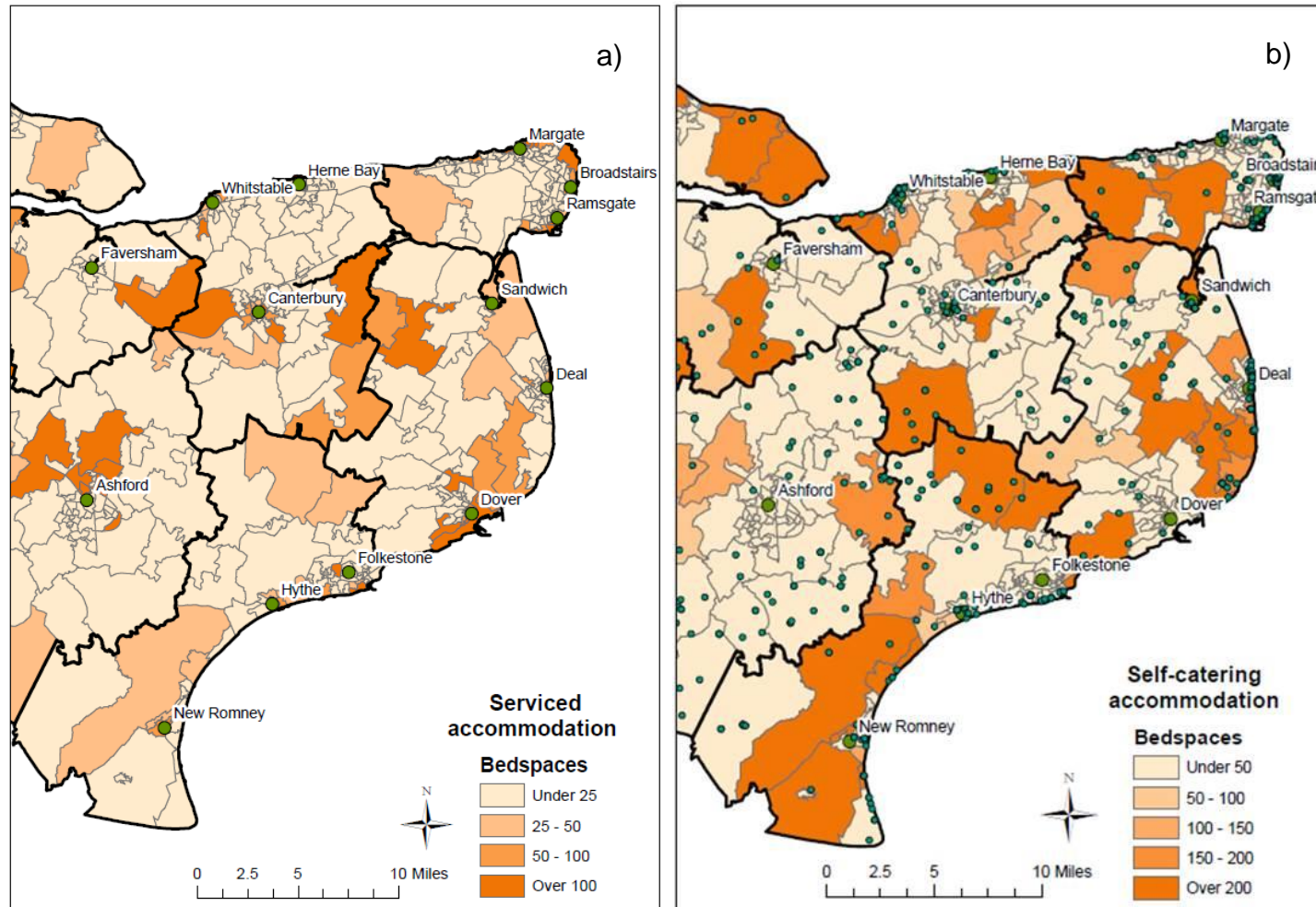
Figure 8.2 - Spatial distribution of accommodation stock based on 2011 VisitKent database (East Kent)

Overall provision (number of bedspaces) shown at an LSOA Level for a) Serviced Accommodation, b) Self-catering accommodation (including camping and caravanning). Camping and caravanning bedspaces are based on an average pitch occupancy of 3 people.

Table 8.2 - Occupancy rates (proportion of the accommodation stock occupied) based on 2011 data.

	Serviced (rates used for guest house/B&B shown)	Self-catering units (includes statics and lodges)	Camping and caravanning (Touring Pitches)
January	27	41	5
February	37	60	5
March	36	58	10
April	52	48	40
May	50	57	64
June	68	67	70
July	76	54	76
August	72	95	100
September	70	74	46
October	59	75	34
November	44	65	5
December	35	61	5

Thomason and Keeling (2012) note that, at the time of writing, there existed no specific monitoring or information on the performance of the self-catering or camping and caravanning sector in Kent. As such, no source of local data is available which identifies occupancy rates for self-catering accommodation or camping and caravanning in 2011, either for Kent, or a wider spatial scale such as the South East. Unlike Cornwall (Chapter 5), this form of data has not been collected by VisitKent or Tourism South East (TSE), and does not form part of the national occupancy survey compiled by VisitEngland. However, in April 2012, VisitKent began collecting data on occupancy rates among the self-catering sector using a sample of 382 businesses (VisitKent, 2013b). Occupancy rates collected by VisitKent between April 2012 and March 2013 have been used (VisitKent, 2013b). This was the first season in which this data was collected. Since 2012 exhibited a different pattern of visits (particularly driven by different timing of Easter, weather and the Olympics), these occupancy rates should be used with caution. In the absence of suitable data collection for the year of interest, it is necessary to supplement with data that is indicative of the trends, and could be updated as additional data becomes available.

Similarly, occupancy rates are not collected at all for camping and caravanning accommodation by VisitKent or Tourism South East and they do not form part of the national occupancy survey and are not made available by major organisations in this sector such as the Caravanning and Camping Club. It is hoped that this form of data collection may be enhanced in the near future by VisitKent, particularly since Thomason and Keeling (2012) note that within Kent, occupancy during summer weekends is likely to be exceedingly high, particularly for camping pitches, with many sites having to turn potential custom away. In the interim period, indicative figures have been used, which reflect occupancy rates for this form of accommodation in the South West (see Chapter 5). Unfortunately these data are most recently available for 2010, but have been amended by the author to represent likely occupancy rates for Kent in 2011, based on information on overall visitor numbers, local events, weather and other factors as outlined in the VisitKent Business Barometer (VisitKent, 2012).

Having inferred accommodation utilisation using occupancy rates, attention now turns to estimating expenditure associated with an occupied accommodation unit. In common with the situation in Cornwall, there is no local survey data that provides even an indication of visitor spend specifically on food and drink. Whilst it would, in theory, be possible to carry out a survey of visitors, this chapter aims to develop techniques and methodologies that can be applied relatively easily by location planning teams working within major retailers, where the time and resource does not exist. Consequently, and as outlined previously, this thesis seeks to use readily available datasets wherever possible. As such, and based on a range of reports and insight (which are documented fully in Chapter 5), this chapter applies the same expenditure rates as those used for Cornwall, shown once again in Table 8.3

In common with Chapter 5, Table 8.3 incorporates estimates of the weekly expenditure associated with an occupied room in hotel or guest accommodation. In Chapters 3 and 5 it was noted that, in terms of the visitors themselves, grocery expenditure associated with an overnight stay in these forms of serviced accommodation is likely to be minimal. However, it was suggested that some visitor induced grocery expenditure would be present, driven by expenditure by operators who may purchase guest breakfast items from their local supermarket. In the absence of any previous research a small survey was attempted in Cornwall, using the limited resources available to the author. Given the very low response rate, findings were not incorporated in Chapter 5, and instead rates for Kent were applied as outlined within the following paragraphs.

With the support of VisitKent and their network of accommodation operators, it has been possible to conduct a survey of accommodation operators to support this research. VisitKent administered a web-based survey, incorporating questions requested by the author, alongside questions of interest to the VisitKent team (based on local product sourcing to support their 'Kent Breakfast' campaign). 33 establishments responded, ranging from a 100 unit holiday

park through to a 1 room B&B. This represents approximately a 10% response rate. After discounting those establishments that did not represent serviced accommodation, 18 establishments remained. Even with the support of a tourist organisation and their network of accommodation providers (who routinely respond to their requests for information) the response rate was low. An incentive in the form of an entry into a prize draw organised by VisitKent and a number of reminder emails sent by their team still yielded a disappointing response. This serves to highlight the considerable difficulty in obtaining reliable survey information in this sector and reinforces the need to rely on information sourced from large-scale national or regional surveys in order to inform an understanding of the local demand side.

Table 8.3 - Expenditure rates applied to estimate visitor expenditure driven by utilisation of commercial accommodation

	Low/Fringe Season *(Sept-May)*	*Peak Season* *(June-Aug)*
Tourist Campsites	£66.08	£78.23
Holiday centres and villages	£71.14	£79.76
Rented cottage/apartment	£96.18	£107.80
Hotel/guest accommodation	£27.30	£27.30

Useable responses relate to 18 establishments with a total of 101 guest rooms, predominantly in small establishments (17 out of the 18 establishments are less than 10 rooms). With the exception of 3 establishments that are closed in the low season, all establishments are open all year round, with an average occupancy rate of just over 50%. 15 of these establishments provide a full breakfast service, with an average of 5 breakfasts per establishment per night. 7 establishments report that they purchase food/drink supplies directly from a wholesaler, whereas only 5 use a supermarket as a source of guest food and drink. On average, and after accounting for the size of each establishment, respondents claim to spend £3.89 per guest per night on food and drink, varying from £1 per guest per night in a 10 room establishment, through to a £8 per guest per night in a smaller establishment. In the absence of any further subdivision (and for the purpose of grocery demand estimation), it is assumed that half of this expenditure is attracted to local grocery stores. Consequently, £1.95 per guest or (assuming double occupancy) £27.30 per occupied room per week has been used to calculate induced visitor spend by B&B, and guest house owners for use in demand estimation. Induced expenditure has not been added for chain hotel accommodation (e.g. Premier Inn, Hilton, Ramada Jarvis etc.), as it is reasonable to assume that these larger establishments will

purchase almost all their inputs through established agreements direct from suppliers, and are unlikely to purchase inputs from local grocery stores.

Having considered expenditure associated with all forms of commercial accommodation, second home owners and VFR hosts are now considered. Spatial and seasonal patterns of visitor expenditure as driven by commercial accommodation are outlined in section 8.4.

8.3.2   Visits using second home accommodation

In common with the modelling carried out in Cornwall, second home data has proved tricky and problematic to source. Even with the support of Visit Kent and their well-established contacts at Kent County Council, it was not possible to obtain council-tax records identifying, at the small-area level, those dwelling that are second homes. Communities and Local Government (CLG) attempted to collect a snapshot of data on vacant and secondary dwellings from Local Authorities on 31st March 2008 (Communities and Local Government, 2008). Local Authorities were under no obligation to provide this information and, whilst this information was available for the study area, clear inconsistencies in reporting are evident. For example, the Canterbury District (home to the popular Herne Bay and Whitstable resorts) recorded only 51 second homes, known to be a considerable underestimation (431 such dwellings were recorded in the 2001 census). As such, it has been necessary to rely on data from the 2001 census[36] which includes counts of the number of dwellings that are recorded as second homes. Across the four study districts, a total of 2,476 units are recorded.

In common with Chapter 5, utilisation rates for second homes are also difficult to obtain and cannot be easily inferred. As noted in Chapters 3 and 5, second home usage varies considerably, with some owners using their second home most weekends and holidays, and others only using it during the summer. Many second homes will also be rented and therefore occupied heavily between March and October, whereas others may lie empty for much of the year. In the analysis which follows, and in common with Chapter 5, it has been assumed that second home utilisation follows a similar pattern to self-catered cottage/apartment occupancy rates. It remains clear that second home ownership and utilisation is an under-researched area. Nonetheless, for the purpose of grocery expenditure estimation among location planning teams, it is considered that the approach used here (relying on census data) is adequate. As small-area counts of second-home units become available from the 2011 census it will also be possible to obtain more timely estimates of small-area second home counts. It is strongly recommended that future research by organisations such as VisitKent should seek to understand more about the utilisation and associated expenditure linked with secondary dwellings.

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[36] 2001 Census Table UV53

8.3.3 Overnight and day visits to friends and relatives

Chapter 3 outlined that the VFR market has grown rapidly and is often a major motivator and trip generator, second only to holiday tourism in terms of market size. In particular, this market is known to be important in Kent, accounting for around 2.3m overnight trips per year (plus a number of day trips), and is the second most valuable visitor sector (after holidays), generating around 34% of overall visitor spend in Kent (TSE Research, 2012). As outlined within Chapters 3 and 5, VFR tourism is known to generate considerable host spend in the local economy, especially on groceries. Nonetheless, estimating actual numbers or the spatial distributions of these forms of visit is tricky.

As part of SusTRIP, Kent benefits from a detailed survey of VFR tourism in the county. Carried out in January/February 2011 (The Tourism Company, 2011), the survey aimed to collect data on the VFR market to inform marketing campaigns. The Kent VFR survey was based largely on primary research and considered both hosts and the visiting friends and relatives themselves. The survey findings have been discussed in detail within Chapter 3 providing very useful and comprehensive evidence that VFR tourism (both day and overnight visits) generate additional host spend in the local community. Unfortunately, the survey does not quantify that spend. Since the survey of hosts is based specifically on those that have hosted visitors in the past year, it is of little use for understanding actual numbers of nights hosted across the entire residential population and housing stock. The survey is also little help in identifying the seasonal pattern of visits, or average length of stay, since hosts were specifically asked to recall the most recent VFR trip. Given the timing of the survey (January and February), results are likely to be skewed by the high number of visits that will undoubtedly have taken place over Christmas.

The Cambridge Model outputs include estimates of additional annual expenditure by VFR hosts (TSE Research, 2012). In common with Chapter 5, these estimates have been used in conjunction with estimates of the seasonal and spatial distribution of visits. Unlike Cornwall (where the outputs were available only at a county level), modelled outputs are reported at the local authority district level. This allows the likely spatial pattern of additional small-area grocery spend to be modelled, taking account of specific district level rates. Recall also that the Cambridge Model estimates incorporate all additional spending by hosts when hosting both overnight and day visitors. This approach assumes that spend associated with hosting VFR visitors can be distributed evenly across the housing stock. Whilst it is acknowledged that some households will inevitably host more visitors than others, it provides an indication of the likely spatial pattern.

Across the study area, the Cambridge Model estimates a total additional host spend of over £65m per year (TSE Research, 2012). Assuming (in common with Chapter 5), that 26% of host expenditure represents groceries (Briggs, 2002), then a total of over £17m per year (or an average of around £325,000 per week) additional grocery spend exists. At a district level

this ranges from an average of around £60,000 additional grocery spend (per week) in the Shepway district, to over £100,000 per week in the Canterbury district. In common with the approach used in Chapter 5, this expenditure has been distributed spatially across the housing stock on a district-by-district basis at the OA level. As such, on an OA-by-OA basis the additional grocery expenditure by hosts can be identified.

The OA level host spend has been distributed seasonally based on the self-reported starting month for VFR trips (drawn from regional GBDVS and UKTS data) and calculated on a weekly basis, as applied in Chapter 5. In addition, and in contrast to the approach used in Cornwall, an additional seasonal distribution of VFR trips has been incorporated for all VFR trips hosted by student households in the Canterbury District. Canterbury is home to over 40,000 students (across two institutions) (HESA, 2012). In a study of students as VFR hosts at the University of Swansea, Bischoff and Koenig-Lewis (2007) identified that students act as important hosts in university cities, and that these visits exhibit an unusual temporal distribution. Due to term dates, students may only be residing in cities such as Canterbury for around 9 months of the year, thus concentrating visits into that period and reducing the number of host households outside of term time.
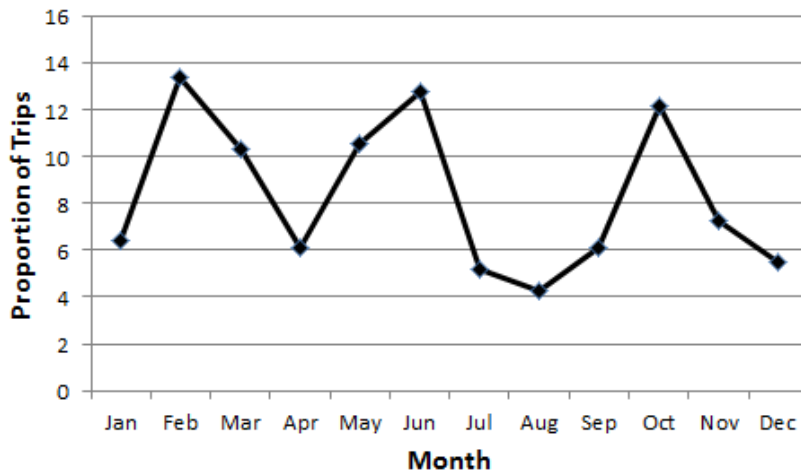
Figure 8.3 - Seasonal distribution of VFR visits where students act as hosts

Source: adapted from (Source: adapted from Bischoff and Koenig-Lewis, 2007, p473)

Student households in Canterbury (identified at the OA level and also incorporated within the residential housing stock and demand estimation)[37] have been identified and (in common with the non-student households) assumed to be potential hosts of VFR visitors. However, a separate temporal distribution for these visits and their induced host spend has been applied, based on the surveyed distribution of VFR trips from Bischoff and Koenig-Lewis' (2007) study. The seasonal distribution of trips is shown on Figure 8.3, and clearly highlights the importance of term-time visits which peak in February and October/November, plus a post-

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[37] 2011 Census (Table QS113EW)

exam peak in June. Due to the high number of students away from their university city in August, this actually represents the month with the lowest proportion of this form of visit, in contrast to traditional VFR tourism with non-student hosts.

Having incorporated all forms of expenditure associated with overnight visitors, including induced host spend, attention now turns to estimating additional grocery expenditure driven by day visitors.

8.3.4 Day visitor expenditure

As noted within both Chapters 3 and 5, day visitors also contribute to store-level grocery demand uplift. According to the 2011 GBDVS, Kent attracts around 34m day visitors per year (VisitEngland, 2012), with the Cambridge Model outputs suggesting that 16.3m of these visits are to the four East Kent study districts (TSE Research, 2012). However, almost three quarters of these day visits are carried out by day visitors who are Kent residents (TSE Research, 2010). As such, these visitors are unlikely to exhibit a high grocery spend (on an individual basis) due to the ease of bringing food and drink from home if not planning to eat out. Additionally, based on GBDVS data for the South East[38], 32% of these day visits are thought to represent VFR visits. The host expenditure associated with these visits has been incorporated in the estimation of VFR host spend in section 8.3.3.

21% of these visits (almost 3.5m) are inferred to represent a general day out (VisitEngland, 2012) and, in common with Chapter 5, these visits are thought to generate some grocery expenditure, predominantly snack-foods for immediate consumption or limited top-up shopping to take home. In the absence of local insight, GBDVS expenditure rates have been applied based on a surveyed total spend of £34 per party per day visit (within the south east) (VisitEngland, 2012)). The GBDVS identifies that 17% of this expenditure (£5.78) commonly represents food and drink (purchased from shops or take-aways for immediate consumption (VisitEngland, 2012). In the absence of any further breakdown, it has been assumed that half of this expenditure (£2.89 per visit) may be attracted to grocery stores, representing a total grocery spend attributable to day visitors of over £10m per year.

This form of visitor expenditure also requires spatial and temporal distribution across the tourist season and study area for inclusion within the modelling process. Once again the seasonal distribution is derived from the 2011 GBDVS, and has been extracted by the author as a cross-tabulation using their online data browser. The proportion of day visits to towns, cities and resorts in the South East region by month has been extracted, as shown in Figure 8.4. Trip related expenditure has been further disaggregated by week for compatibility with the existing residential and visitor demand estimates.

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[38] Extracted from their online data-browser via http://dservuk.tns-global.com/gbdayvisitsLightEngland/
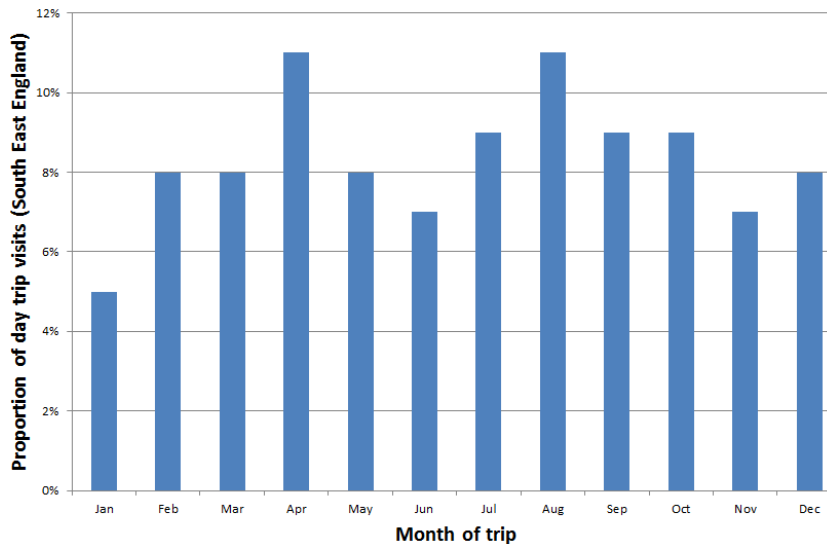
Figure 8.4 - Seasonal distribution of day trip visits to destinations within South East England (2011).

Derived from GBDVS 2011[39]

Day visitor expenditure also requires spatial disaggregation so that the available day visitor spend is attached to individual OAs representing the major destinations attracting day visitors within the study area. A total of 12 major destinations are used (see Table 8.4). These resorts are likely to attract many of the day visitors and the list of destinations and their share of overall day visitors are based on results provided by VisitKent from their 2011 'conversion research', a web-administered questionnaire, targeting individuals that had previously requested information about Kent. Based on 2,423 responses, the stated destinations visited have been used to identify relative proportions of day visitors by destination as shown in Table 8.4. Canterbury accounts for over a fifth of all day trip visits. Canterbury City Council (2013) notes that the visitor economy in the city is driven by its cultural and heritage offer, and is a significant contributor to the wider economic and tourist value of East Kent. It is thus unsurprising that the city is such an important attraction for day visitors. Nonetheless, coastal resorts such as Broadstairs, and towns such as Dover also represent important destinations for these forms of visitor, generating considerable additional grocery demand in these areas. Section 8.4 explores the spatial patterns evident in this form of visitor demand, along with expenditure derived from local residents and overnight visitors.

8.4   Seasonal and spatial patterns of grocery demand in Kent

Section 8.3 identified the stock and utilisation of commercial accommodation and second/holiday homes, applying grocery expenditure rates from survey data based on the methodology developed and employed in Chapter 5. Expenditure associated with day

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[39] http://dservuk.tns-global.com/gbdayvisitsLightEngland/

visitors and VFR hosts has also been incorporated, with the latter benefitting from district level data available via the Cambridge Model and disaggregated at the OA level. Although not discussed within this chapter, residential grocery demand has also been estimated and in common with the modelling employed for Cornwall, uses the methodology outlined in Chapter 5. As such, residential grocery demand has been estimated on a month-by-month basis, accounting for OA level workplace inflow or outflow (redistribution of commuters' expenditure) and outflow of households holidaying elsewhere. Across the study districts, accounting for all residential households, 52 week average residential grocery expenditure equals £13.3m per week (an average of just under £70 per household per week) (Table 8.5). An understanding of the spatial and seasonal patterns of residential demand is essential in order to be able to model overall grocery demand across the study area, as carried out in sections 8.5 and 8.6.

Table 8.4 - Spatial distribution of day visitor expenditure to 12 major day visitor destinations in East Kent.

Proportion of day visitors by resort derived from data supplied by Visit Kent from their 2011 'Conversion Research'.

	Proportion of day visits	*Number of day visits (per week)*	*Day visitor grocery expenditure (£ per week) August*
Canterbury	0.23	20,779	£90,273
Herne Bay	0.07	4,829	£20,978
Whitstable	0.03	2,069	£8,990
Dover	0.11	7,588	£32,965
Deal	0.06	4,139	£17,981
Sandwich	0.03	2,069	£8,990
Margate	0.08	5,518	£23,974
Broadstairs	0.12	8,278	£35,962
Ramsgate	0.08	5,518	£23,974
New Romney	0.03	2,069	£8,990
Hythe	0.06	4,139	£17,981
Folkestone	0.10	6,898	£29,968
Total	**1**	**73,894**	**£321,027**

Additional spend linked to visitors accounts for £1.5m per week (52 week Average), rising to over £2.5m per week in August. The additional expenditure available in August represents a considerable sum, and accounts for almost 14% of available grocery expenditure at this time of year. Table 8.5 highlights that visitor spend is driven largely by the contribution of overnight visitors using commercial accommodation and by day visitors. The overall contribution of visitor demand is less than in Cornwall, where visitor demand accounted for almost 32% of available grocery spend (in August). Nonetheless, the importance of visitors using commercial accommodation in driving this form of demand is clearly evident in East Kent and is in common with Cornwall. Consequently, even where location planning teams lack resources, it is strongly suggested that attempts should be made to account for demand associated with visitor accommodation during the modelling process, as discussed further in Chapter 9.

Whilst the overall volume of demand uplift is lower in East Kent than in Cornwall (£2.6m in August within Kent as opposed to £7.3m for the corresponding period in Cornwall), clear spatial and seasonal clusters of visitor grocery demand are exhibited: see Figure 8.5, especially around Dover, Canterbury, Broadstairs, Deal and Hythe/New Romney. Figure 8.5 highlights that Dover and Canterbury exhibit year-round spatial clusters of visitor demand, undoubtedly driven by the former's role as a major transport hub, and the latter as an historic city popular with visitors year round, including those en-route to or from the channel ports. By contrast, peak season clusters of demand on the coastline between Deal and Dover, and around Broadstairs, Hythe and New Romney are clearly evident, driven by the provision of self-catering visitor accommodation in these areas. Sections 8.5 and 8.6 model the impact of these seasonal and spatial variations in grocery demand at a store-level.

8.5   Using the disaggregate SIM to model grocery supply and demand in East Kent

Section 8.4 has outlined the seasonal and spatial patterns of grocery demand in East Kent using the seasonal demand estimates produced in section 8.3. Whilst the overall degree of demand uplift driven by visitors during the peak season may be less than the corresponding uplift in Cornwall, clear seasonal and spatial variation in overall grocery demand does exist. In particular, peak-season spatial clusters of grocery spend are evident around key accommodation sites and major attractions. This section seeks to use these small-area demand estimates to identify the store-level impact of demand fluctuations, demonstrating that these expenditure estimates can be used to generate robust revenue predictions for grocery stores in East Kent.

Table 8.5 -Total available grocery expenditure by origin – comparison of January, August and 52 week Average (2011)

	Available Grocery Expenditure			*Proportion of available Grocery Expenditure*		
	January	August	52 week Average	January	August	52 week Average
Local Residents	£13.6m	£13.0m	£13.3m	96.4	86.2	91.4
Overnight visitors using commercial accommodation	£65,397	£780,000	£318,000	0.5	5.2	2.2
Second home owners	£86,300	£217,495	£162,258	0.6	1.4	1.1
VFR Hosts	£231,000	£441,000	£350,000	1.6	2.9	2.4
Accommodation operators	£59,000	£154,000	£110,250	0.4	0.7	1.1
Day visitors	£288,000	£1,052,000	£538,000	0.5	3.5	1.8
Total	**£14.3m**	**£15.6m**	**£14.8m**			
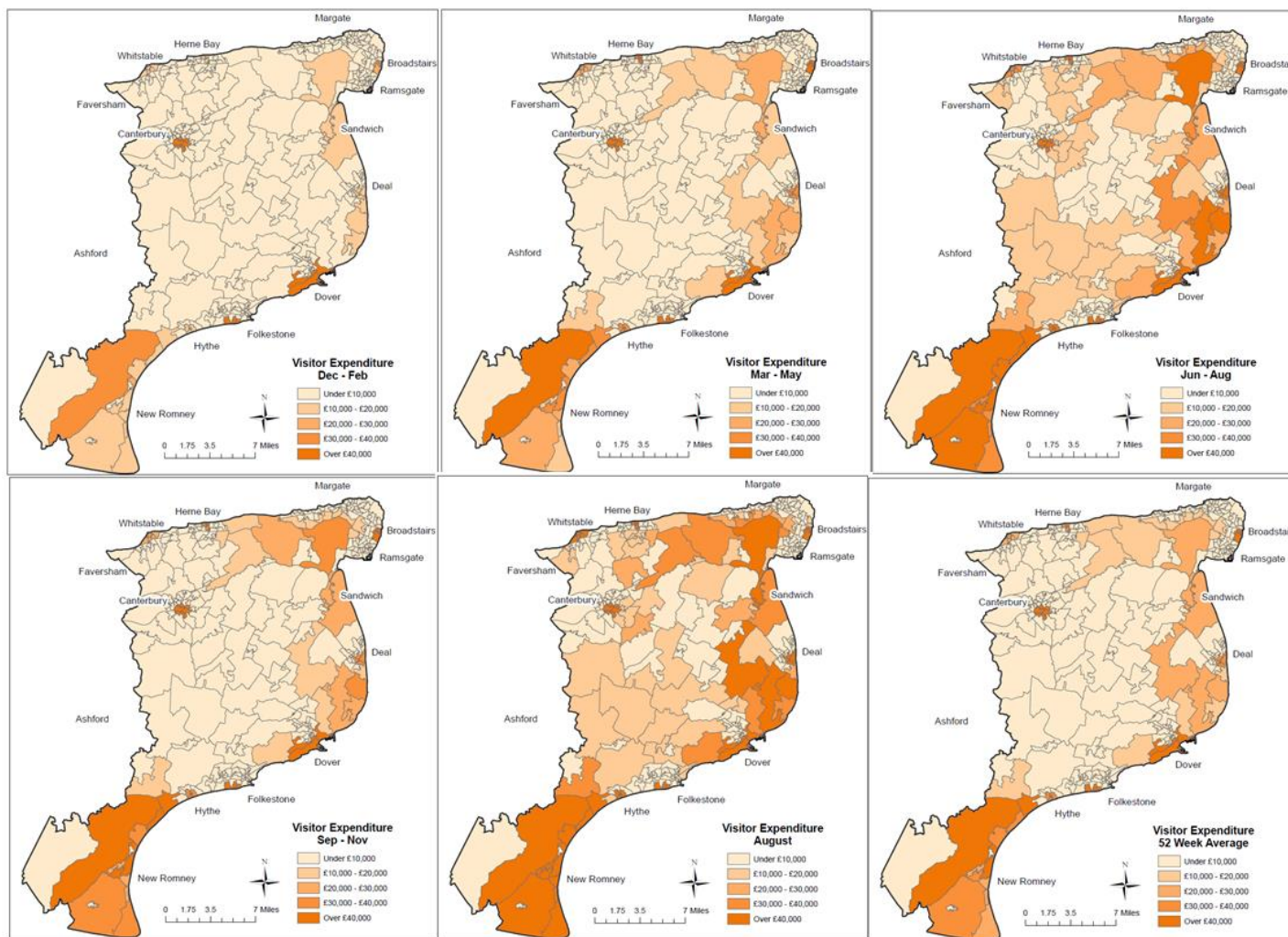
Figure 8.5 - Seasonal visitor demand estimates (average weekly spend) (2011)

a) Winter (Dec-Feb), b) Spring (March – May) c) Summer (June – Aug) d) Autumn (Sept - Nov), e) August (peak school summer holiday) and f) 52 Week Average

8.5.1   Modelling supply, demand and interaction

The SIM takes the same structure and form as the disaggregated SIM which was developed for use within Cornwall (Chapter 6), and incorporates demand side input data as documented in section 8.3. This section briefly recaps on the characteristics of the model (equation 8.1) and outlines the supply side data used. The calibration and validation routine is then discussed with reference to data relating to Sainsbury's stores in East Kent, but this section does not seek to repeat the discussion surrounding model development which can be found in Chapter 6. However, for clarity, recall that the SIM, which has been disaggregated on both the demand (consumer type) and supply side (retail brand), takes the form:

$$S_{ij}^k = A_i^k \, O_i^k \, W_j^{\alpha^{kn}} \, exp^{(-\beta^k C_{ij})} \qquad (8.1)$$

Where: S_{ij}^k represents the predicted expenditure flow between zone $_i$ and store $_j$ by consumer of type k.

A_i^k is a balancing factor which takes account of competition and ensures that all demand from zone $_i$ by consumer type k is allocated to stores within the modelled region. The balancing factor thus ensures that:

$$\sum_j S_{ij}^k = O_i^k \qquad (8.2)$$

 It is calculated as:

$$A_i^k = \frac{1}{\sum_j W_j^{\alpha^{kn}} \, exp^{(-\beta^k C_{ij})}} \qquad (8.3)$$

O_i^k is a measure of the demand or expenditure available in demand zone i by consumer of type k.

W_j reflects the overall attractiveness of store j, whilst α^{kn} represents the additional or perceived relative attractiveness of store j for consumer type k and by store type (brand) n.

C_{ij} is the distance (although in this application, travel time is used) between zone i and store j, and incorporates the distance deterrence/decay parameter $exp^{-\beta^k}$ for consumers of type k.

In common with Chapter 6, collaboration with Sainsbury's gives rise to the provision of flow data allowing model calibration against empirical data. Coupled with the inclusion of seasonal visitor demand which has been previously omitted from this form of modelling, the

SIM represents a powerful tool for store location planning across the study districts. Demand incorporates residential and visitor expenditure at the OA level, with average weekly grocery spend calculated for 12 months of the year (each of which can be modelled separately), and a 52 week average, all for the year 2011. On the supply side, a total of 92 stores fall within the study area, derived from a database held by GMAP (extracted via their Microvision software) and updated by the author using Sainsbury's knowledge of competitor networks, local planning applications and local retail assessments (e.g DTZ, 2011; KCC, 2010).

23 smaller Co-Op and Budgens stores, all under 2,000 Sq Ft have been omitted. Their limited size and ranges (plus local competition from larger stores) means they will serve a minor role in local groceries provision. Large stores located in the nearby town of Ashford, which is outside the study area, were also incorporated. These stores are within easy reach of consumers living to the west of the Shepway and Canterbury districts and form an important part of the foodstore provision (see Figure 8.7 and Figure 8.6). Stores within the model range from a 2,000 Sq Ft Co-Op to a 78,100 Sq Ft Tesco store, between them providing a total floorspace of over 1.3m Sq Ft. Figure 8.7 and Figure 8.6 highlight that retail provision is heavily concentrated towards major urban areas, such as Canterbury and Folkestone, with all the major retailers well-represented in these areas. Provision is more dispersed across the Shepway and Dover districts, with smaller stores serving settlements such as New Romney, Hythe, Deal and Sandwich, all popular among visitors.

In common with the approach used in Chapter 6, store floorspace and store brand are used to drive store attractiveness in the model via the $W_j^{\alpha^{kn}}$ term. The alpha values used are once again derived from the location quotients produced by Thompson *et al.* (2012) using Acxiom consumer survey data (see section 6.4.2) in an attempt to reflect the relative attractiveness of different brand/fascias by consumer type. The alpha values applied here are the same as those used in Cornwall, documented fully in Chapter 6 and Table 6.3.

Interaction data again takes the form of road travel times, provided by Sainsbury's and extracted from MapInfo Drivetime (version 7.1) software using the 'Street Pro' (2011 edition) road network. Based on Sainsbury's usual approach, 'out-of-the-box' settings were used (e.g. no user defined speed matrices were applied) and the quickest off-peak route (rather than the shortest) were used. In common with Chapter 6, a range of β values were also used to control the relative importance of travel time (as the interaction parameter) by consumer group. β again varies by household type, using the OAC classification as a proxy for both income and car ownership. Three β values have been applied, representing the behaviour of high, mid and low income consumers and are informed by Thompson *et al.*'s (2012) study of consumer grocery shopping habits and interaction patterns.

Having briefly outlined the characteristics of the model and input data, section 8.5.2 considers model calibration.

8.5.2 Model calibration

In common with the approach used in Chapter 6, model calibration and validation takes place using store and consumer-level data provided by Sainsbury's. Whilst not seeking to repeat the discussion from Chapter 6, the calibration process is briefly outlined below for clarity. Sainsbury's operate eight stores within the study area, six of which are used as part of the model calibration process, with an additional two stores not forming part of the calibration data, but used to validate the model's revenue predictions. The stores used are shown in Table 8.6, and are split across the districts that make up the study area. The six calibration stores range in size from around 11,500 Sq Ft through to over 30,000 Sq Ft (average 26,000 Sq Ft) and provide an ideal range of stores against which to calibrate the model, due to the variety of sizes, store and location types. Two additional stores (both located in Folkestone) are used for validation only, since flow data from the loyalty card scheme has not been provided. These are long-established stores, one (which is somewhat dated) serving the town centre, with the second representing Sainsbury's largest store in the study area, located on an out-of-town industrial park and retail complex adjacent to the M20 motorway.

Known consumer flows are taken from the company's own analysis of its Nectar card data, with all flows used relating to the 2011 trading year and representing 52 week averages. Calibration has been carried out using these observed Nectar card flows, and the 52 week average flows predicted by the model. The model operates at the OA level, and both the predicted and observed flows have been aggregated to LSOA level for comparison. The use of LSOAs accounts for the very low flows observed in some OAs and allows for a more meaningful comparison of flows.

As shown in Chapter 6, calibration seeks to minimise the difference between observed (ATD^{Obs}) and predicted (ATD^{Pred}) average trip distance. An iterative procedure was used, whereby a series of incremental β values were cycled through by the model, with the value of ATD^{Pred} / ATD^{Obs} recorded. The iterative procedure continued, using increasingly narrow ranges and smaller incremental values, in order to identify β values that most closely replicated the observed flows. Recall from Chapter 6 that although road travel time is used to operationalize the model at the OA level, road travel time data is not held at the LSOA level, and so straight line or 'as-the-crow-flies' distances (from LSOA centroids to store postcodes) have been used for the comparison of ATD.
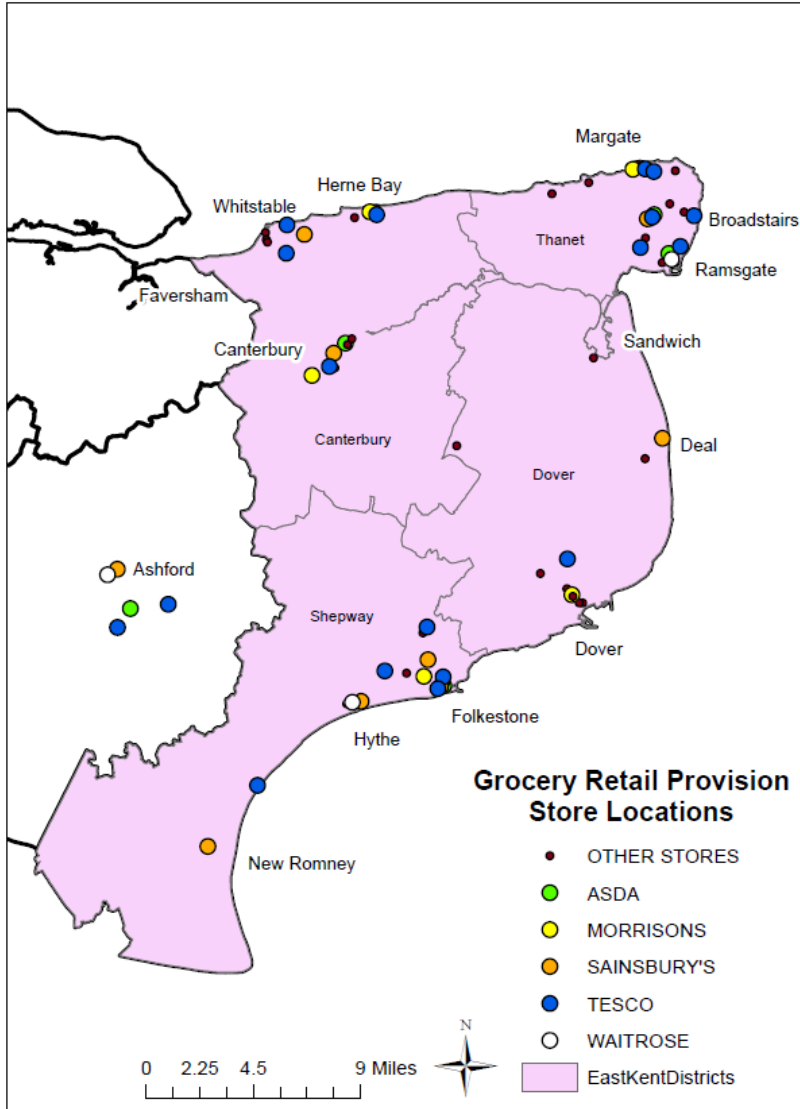
Figure 8.6 - Grocery retail foodstore provision - East Kent by retailer
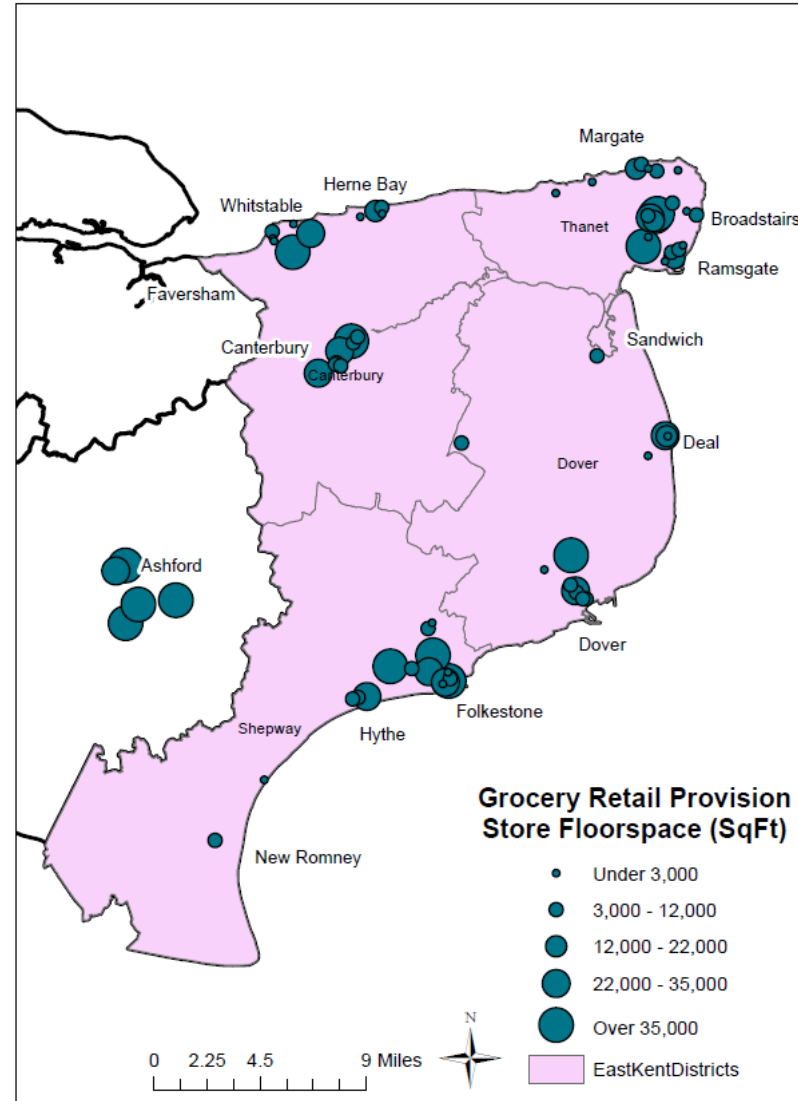
Figure 8.7 - Grocery retail foodstore provision - East Kent by floorspace

Table 8.6 - Characteristics of stores used for model calibration

Store	Store Type	Floorspace Sq Ft
Stores used to calibrate model parameters against known consumer flow data		
Canterbury	Large-format edge-of-centre in major city	31,000
Deal	Mid-sized edge-of-centre in a coastal town	24,000
Hythe	Edge-of-centre in market town	30,000
New Romney	Town-centre/edge-of-centre in a tourist resort	11,500
Thanet	Large-format out-of-town on a retail park serving urban areas	32,000
Whitstable	Out-of-town serving a coastal town popular among visitors	26,000
Stores used for validation of modelled revenue predictions (and not used as part of the calibration dataset)		
Folkestone (Town Centre)	Mid-sized store located on the edge of the established town centre	23,000
Folkestone (Out-of-town)	Superstore on an out-of-town industrial and retail park adjacent to M20 motorway	49,000

On a store by store basis, the value of ATD^{Pred} / ATD^{Obs} is shown in Table 8.7, with values above 1 identifying that ATD has been over-predicted by the model (and vice-versa). Table 8.7 illustrates that the model is performing well, with all stores exhibiting ATD^{Pred} / ATD^{Obs} that converges towards the target value of 1.0. Taking the β value (0.19 for mid income consumers) which minimises the overall difference between observed and predicted flows, the model has been able to predict ATD to within 5% at all stores. The only exception is Thanet, where the store's location on a major retail park and very popular out-of-town shopping centre is likely to attract consumers from a slightly broader catchment than captured by the model. Nonetheless, the ability of the model to predict overall consumer flows (at the LSOA level) to within an average of 3% of reality is very encouraging, especially across such a range of different store types and locations.

Given that the model is able to replicate known characteristics of consumers' shopping trip making behaviours to a very acceptable level of accuracy, attention now turns to assessing the model's ability to correctly replicate the magnitude of those flows. Taking the approach outlined in Chapter 6, predicted expenditure flows between demand origins are compared to observed flows for the six Sainsbury's stores that are used for calibration. As justified fully

in Chapter 6 (along with supporting equations), R^2 (or the coefficient of determination) and SRMSE (standardised root mean square error) are used here.

Table 8.7 - Observed and predicted ATD (straight line distance) for East Kent study stores - based on 52 week flows.

ATD	Straight line distance (km) – LSOA Level		
	ATD^{Pred}	ATD^{Obs}	$\dfrac{ATD^{Pred}}{ATD^{Obs}}$
Canterbury	3.59	3.49	1.03
Deal	2.13	2.24	0.95
Hythe	5.39	5.65	0.95
New Romney	2.88	2.92	0.99
Thanet	3.48	3.92	0.89
Whitstable	3.15	3.18	0.99
Average	3.43	3.56	0.97

The model is able to replicate observed flows originating from residential households to an impressive level of accuracy, with an R^2 at 0.86 and a SRMSE of 0.02, in line with its performance in Cornwall. In particular, and as noted in Chapter 6, Harland (2008) demonstrated that SRMSE (with a lower limit of zero, representing complete correspondence between observed and predicted flows) is particularly sensitive to discrepancies in flow volumes and to their position within the matrices of observed and predicted flows. The particularly low SRMSE value suggests that this model is operating well and is able to replicate, with some accuracy, the observed flows (which represent 52 week averages). It should be noted, however, that observed (Nectar) flow data is only held for residential demand, and as such, only the residential component of the model can be calibrated via ATD and GOF statistics.

In order to evaluate the model's performance after incorporating visitor demand, store-level revenue must be considered. Overall fluctuations in store revenue are the only indicator of seasonal sales fluctuations that are available for these stores. Hence, given that residential demand has been calibrated to an acceptable level of accuracy, visitor demand can be incorporated within the model and the model's overall performance can be evaluated against its ability to predict overall store revenue, at both an aggregate (52 week average) and also temporally disaggregated (monthly) basis. If, after inclusion of visitor demand, the model can predict store revenue to an acceptable level of accuracy, we can be confident that it is able to reproduce consumer behaviours with some accuracy too, even if those individual

behaviours (in the case of visitors) are actually unknown (since no observed information is known on consumer origin within the study area for visitors).

Table 8.8 shows the ratio of observed to predicted store revenue at the six Sainsbury's study stores, considering a 52 week average, alongside weekly average on a month-by-month basis. In all cases, a value of 1.0 demonstrates exact correspondence between observed and predicted store revenue; a value above 1 demonstrates that the model has over-predicted revenue; whilst a value of less than 1 demonstrates an under-prediction. Table 8.8 suggests that the model is able to predict 52 week average revenue to a very promising level of accuracy, with five of the six stores predicted to within 5% of recorded store sales (food and drink revenue) on a 52 week average basis.

The Hythe store revenue is consistently under-predicted by an average of 7%. This store began trading in February 2011, and as such, the trading data may exhibit an apparent overtrade at this store as customers try out the new store. The model's slight underestimation of ATD for this store (Table 8.6) suggests this may well be the case, with consumers travelling further than the model would expect in order to try the new store. The town already benefits from a very well established and popular Waitrose store, and it would be anticipated that this new store will settle into an established trading pattern over time. Indeed, with the exception of November and December (Christmas uplift), the degree of under-estimation is noted to fall during the first 9 months of trading at this store. Likewise, the accuracy of modelled predictions fluctuates noticeably at the Thanet store too, no doubt driven by the stores co-location with a major out-of-town retail and leisure complex.

On a seasonal basis, the modelled store revenue estimations on a month-by-month basis appear to show close correspondence to the recoded store-level data. In Chapter 6 it was noted that the comparison of observed and predicted revenue on a month-by-month basis should be treated with some caution, since promotions, local roadworks or specific events in-store and nearby (or even in competitors' stores) can all drive very short-term fluctuations in store revenue that could not possibly be predicted by the model, and which would not usually be noticed when considering average weekly revenue on an annual basis. Notwithstanding this point, monthly revenue predictions are commonly within at least 10% of observed revenue (with the exception of Hythe and Thanet).

Nonetheless, and as noted in Chapter 6, the model's predictive capacity can only be evaluated fully by making reference to additional stores that have not been used as part of the model development or calibration. In this case, as shown on Table 8.6 such data is held for two additional Sainsbury's stores in the town of Folkestone, a long-established 23,000 Sq Ft store serving the town centre, and a 49,000 Sq Ft out-of-town store on an industrial park and retail complex adjacent to the M20 motorway, a popular route for tourists heading to the channel ports. Considering the entire 2011 trading year (52 week average), the model overestimates revenue at the out-of-town store by 4%. Given that this store is one of the

largest in the model and that it's trading characteristics are likely to be influenced by its proximity to a major road link, it is very encouraging to be able to estimate revenue with such accuracy.

Table 8.8 - Ratio of observed to predicted store revenue (predicted/observed) for East Kent study stores

2011 Data	C'bury	Deal	Hythe	New Rom.	Thanet	W'stable	Average
Ave[1]	0.94	1.05	0.93	1.03	0.98	0.98	0.99
Jan	0.92	1.09	n/a[2]	0.98	0.96	0.97	0.97
Feb	0.93	1.08	0.89	1.10	0.99	1.00	1.00
Mar	0.90	1.07	0.94	1.03	0.98	0.94	0.97
Apr	0.93	1.01	0.90	0.95	0.94	0.92	0.94
May	0.92	1.07	1.00	1.06	1.00	1.00	1.00
Jun	0.95	1.04	0.98	1.03	0.99	0.98	0.99
Jul	0.98	0.98	0.98	0.98	0.98	0.98	0.98
Aug	1.06	1.09	0.97	1.06	1.07	1.05	1.05
Sep	0.92	1.09	1.02	1.10	1.05	1.03	1.03
Oct	0.98	1.07	0.97	1.10	0.99	1.02	1.02
Nov	0.93	0.99	0.91	1.04	0.86	0.93	0.94
Dec	0.83	0.90	0.81	0.91	0.72	0.85	0.83
Min	0.90	0.98	0.86	0.95	0.86	0.92	0.94
Max	1.06	1.09	1.02	1.1	1.07	1.05	1.05
Range	0.16	0.11	0.16	0.15	0.21	0.13	0.11

Note: **Max**, **Min** and **Range** exclude December (Christmas uplift)

$R^2 = 0.86$ SRMSE $= 0.02$

[1] 52 week average, [2] store opened February 2011

The town centre store revenue is overestimated by 12%. This is likely to be due to the design and characteristics of this store, which are considered a little dated, especially the use of a multi-storey car park above the store as customer parking. This means that the store is unlikely to be used for top-up shopping by passing trade. The store is also somewhat outside the principal centre of gravity of the town centre, which is dominated by a modern (opened 2007) shopping centre (Bouverie Place), comprising a 55,000 Sq Ft ASDA store along with a number of well-known high street retailers, and also benefitting from parking (and situated

adjacent to the town centre bus station). A 2010 retail assessment for the Shepway district actually notes that the district exhibits a negative floorspace requirement, suggesting that there is an over-provision of grocery floorspace following the opening of Bouverie Place (KCC, 2010). As such, it is believed that the apparent under-performance of the Folkestone town centre store (relative to modelled predictions) is driven by a combination of that store's characteristics and strong local competition.

As an additional check of model performance, 52 week average expenditure flows were mapped for a range of stores (including Sainsbury's and competitors) to ensure that flow patterns were logical and of an order of magnitude that would be expected. Average trip cost (in terms of travel time) was also considered on a retailer-by-retailer basis, along with modelled sales densities to ensure that the model outputs conformed to reasonable assumptions about store performance levels (Table 8.9). Table 8.9 identifies that trading intensities average £20.40 (per sq. ft. per week), in line with expectations based on industry data (e.g. J Sainsbury Plc, 2013; Tesco Plc., 2012). Furthermore, ATD is seen to vary by brand, with consumers exhibiting a higher propensity to travel further to reach particular high-end retailers (e.g. Waitrose) and some discount stores (e.g. Lidl), both of which are relatively more attractive to certain consumer types via the alpha parameter, suggesting that the model is performing well.

Table 8.9 - Supply side indicators of model performance – ATD and trading intensity by retailer (52 week average demand)

	ATD (km)	Trading Intensity (Sales/Sq Ft) (£ per week)
Sainsbury's	3.75	19.45
Tesco	3.69	19.72
ASDA	3.83	18.76
Morrisons	3.67	22.07
Waitrose	3.99	19.33
Aldi	3.72	22.68
Lidl	4.19	18.56
Co Op	3.29	23.28
Average	**3.77**	**20.48**

This section clearly highlights that the disaggregate SIM (as developed in Chapter 6) can be operationalized and applied very effectively to an alternative study area where characteristics of supply, demand and seasonal fluctuations may be different. Calibration against Sainsbury's data demonstrates that the use of small-area seasonal demand estimates, coupled

with the disaggregate SIM, can predict store-revenue to within 10% (and in many cases within 5%) of observed values at a variety of store and destination types in East Kent.

Chapter 7 sought to apply the SIM to directly address store location planning concerns on the supply side (e.g. new store openings) and demonstrated that the model is a very powerful tool for predicting store revenue and assessing the impact of network investments on existing stores and competitors. Since Chapter 7 demonstrated the model's application in these contexts very effectively, this chapter does not seek to repeat that form of supply side 'what if?' analysis. Instead, and in order to demonstrate the full potential within the model, this chapter considers a series of demand side scenarios, which are designed to complement the supply side scenarios considered in Chapter 7.

8.6 Modelling demand side interventions

Having demonstrated that the model can predict store revenue to a respectable level of accuracy using seasonal and spatial demand estimates, attention now turns to the ability of the model to handle demand side changes. This section seeks to use the model to identify the impact of proposed or potential demand side changes, such that the volume or seasonal pattern of visitor demand for groceries changes. The model allows such demand side data to be modified and the impact on the supply side at the store-level to be identified, taking full account of resultant seasonal variations. This section applies two scenarios, one identifying the demand and supply side impact of a major development of self-catering accommodation in the Canterbury district (section 8.6.1). A second considers changing demand patterns following an increase in residential occupancy of static caravans in the Shepway district (section 8.6.2).

8.6.1 Impact of new self-catering accommodation provision

As part of the SusTRIP project, a detailed report was commissioned by VisitKent to assess the future opportunities to develop further self-catering and camping and caravanning accommodation provision in Kent, recognising the important role that these forms of accommodation play in generating expenditure in the local economy. In common with Chapter 3, the report notes that the self-catering and camping and caravanning market is highly seasonal, with demand peaking in August, when many sites in Kent are fully booked and often turning visitors away (Thomason and Keeling, 2012). Growth in the popularity of camping and caravanning, particularly as a short break, and the ease of finding sites via the internet means that there is considerable potential to increase this form of accommodation within East Kent.

In spite of a clear demand for these forms of accommodation provision, and a clear commitment to providing additional self-catering accommodation within East Kent, it is difficult to identify a single development proposal which incorporates large-scale visitor

accommodation in order to illustrate the model's capability to handle demand side change. Most schemes are small-scale and involve conversion of individual buildings to provide a handful of accommodation units. Unless these conversions are taking place in sufficient numbers and in geographical-proximity to one-another, the overall demand side impact is very minimal and affords little modelling potential. Only one larger-scale scheme has been identified, comprising development of static caravans, and will be used here as an illustrative example of the type of analysis that can be carried out.

The CCC have expressed considerable interest in refurbishing, remodelling and expanding the park to their standard, improving facilities and incorporating considerable additional static caravans[40]. The draft local plan (Canterbury City Council, 2013 p136) for the Canterbury district states that "The Council will seek to protect existing touring and static caravan tourist sites that make a recognised contribution to attracting and retaining visitors to the District. An emphasis will be placed on encouraging sites to upgrade, renew and extend their offer to retain and grow their offer, and create viable and sustainable touring sites that meet the high standards visitors expect". Specifically with reference to Reculver, the draft local plan claims that "The Council will also continue to encourage the improvement of the environment, and to consider whether the remaining caravan parks could accommodate additional development or activities that would bring further investment and visitors into the Reculver area" (Canterbury City Council, 2013, p139).

The local plan clearly suggests that the provision of additional visitor accommodation may bring further investment into Reculver, and this section seeks to assess the extent to which additional accommodation provision generates additional demand, assessing current levels of demand and modelled consumer behaviour, plus incorporation of additional demand associated with further accommodation provision. The long term ambitions of the CCC (or an alternative operator in the site) in terms of their total proposed investment at Reculver is unknown. For the modelling carried out here, it is assumed that they would seek to introduce 300 additional static caravans. This would generate a total supply of around 500 static caravans in Reculver, in line with the static caravan stock at some of the larger holiday parks in Kent.

Table 8.10 outlines the estimated grocery expenditure originating from Reculver, which is entirely represented by one OA. Expenditure is shown for three different temporal periods, incorporating low, fringe and peak seasons. The estimates in Table 8.10 incorporate local resident and visitor expenditure, and are shown prior to and following introduction of the additional 300 static caravans. The expenditure estimations assume that the additional caravans on the CCC site would achieve occupancy rates that are in-line with the existing

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[40] Planning application CA//11/01504

accommodation provision. It is clear from Table 8.10 that the incorporation of additional static caravans as self-catering accommodation boost grocery demand within Reculver, particularly during August, where grocery demand is estimated to more than double to over £45,000 per week. The increase between low and peak season also becomes more pronounced, with peak season demand representing more than four times the January demand, following investment in accommodation provision.

Table 8.10 - Grocery expenditure originating in Reculver

Average weekly grocery spend	Current Provision	With 300 additional statics	Percentage Increase
Low season (February[41])	£8,172	£10,528	29%
Fringe season (May)	£16,624	£30,426	83%
Peak Season (August)	£22,748	£45,548	100%

The permanent residential population of Reculver (2011 census) is just 88 households, yet it is clear that considerable grocery demand exists within Reculver during the peak tourist season. In spite of clear demand, Reculver lacks provision for grocery shopping, with the nearest store being a 2,000 Sq Ft Co-Op in Beltinge, to the East of Herne Bay, over 2 miles away (Figure 8.8). The SIM suggests that only 5% of consumer expenditure originating in Reculver is attracted to this store. Just over 40% of expenditure is attracted to stores in the neighbouring district of Thanet, or the city of Canterbury (between them comprising seven stores over 30,000 Sq Ft), with the former being over 10 miles away, but easily reached via the primary road network. Only 17% of expenditure is attracted to the nearest large-format store, a 21,000 Sq Ft town-centre Morrisons in Herne Bay, with a further 19% attracted to the large out-of-town Tesco and Sainsbury's stores in Whitstable, also around a 20 minute drive away. Residents and visitors from Reculver are modelled to travel an average of 9.2km to carry out their food shop, more than double the 4.5km that represents the average across the study area.

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[41] February has been used to represent the low season (as opposed to January which has been used elsewhere throughout this thesis) owing to the annual closure of Waterways Caravan Park (part of the existing provision within Reculver) during February.
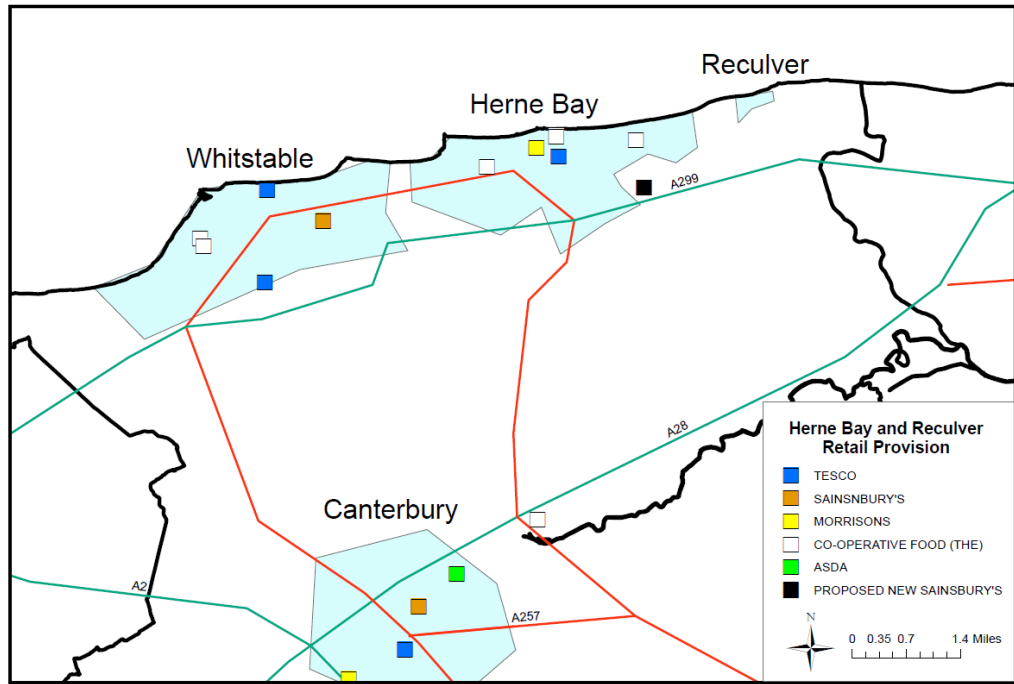
Figure 8.8 - Reculver and Herne Bay - retail provision

As shown in Table 8.10, the additional caravans generate a 100% peak season demand increase within the demand zone. At an individual store-level, the existence of additional accommodation provision has an impact on store revenue and trading characteristics. The eight stores shown in Table 8.11 are the stores that attract the greatest expenditure flows from the Reculver demand zone. The values shown represent the inflow to each store in August from the Reculver demand zone, before and after the introduction of additional caravans. The impact of additional accommodation provision is most pronounced at the 2,000 Sq Ft Co-Op store in the nearby village of Beltinge, where average weekly demand is modelled to increase by almost £1,200 per week.

At the larger stores, all of which are some distance from Reculver, the impact is not so pronounced. Since these stores attract revenue from a wide catchment, the Reculver demand zone only makes up a small proportion of their store revenue. It has already been noted that Reculver (and its spatial clusters of highly seasonal grocery demand) is located in an area currently remote from foodstore provision, thus generating unnecessarily long journeys by visitors and residents within Reculver in order to carry out their food shop. However, in July 2013, Sainsbury's submitted a planning application for a 60,000 Sq Ft Superstore at Altira Park, a housing and leisure development to the east of Herne Bay on a site adjacent to the A299 primary road (Figure 8.8). The model affords considerable potential to identify the impact of new store development (such as the proposed Sainsbury's store) on consumer' trip making behaviours.

Table 8.11 - Expenditure inflow from the Reculver demand zone

		Current Provision (Aug) (£)	With additional caravans (Aug) (£)	Proportion of store revenue (Aug) (with additional caravans) (£)
ASDA	Canterbury	1,251	2,550	0.30
Co-Op	Herne Bay	1,518	3,094	2.24
Morrisons	Herne Bay	3,698	8,002	1.60
Morrisons	Margate	725	1,477	0.31
Sainsbury's	Whitstable	2,452	4,997	0.84
Tesco	Ramsgate	1,072	2,187	0.42
Tesco	Whitstable	1,798	3,667	0.52
Co-Op	Beltinge	1,142	2,328	5.68

The proposed new Sainsbury's foodstore in Herne Bay has been added to the model and consumer flows between demand zones and all stores within the study area have been modelled. The new store is predicted to achieve over a 50% market share in the Reculver demand zone and as such the residents and visitors of Reculver are estimated to travel 4.02km to purchase groceries, less than half the corresponding distance prior to the new foodstore provision. This new store investment considerably improves foodstore provision and access among consumers (predominantly visitors) from an individual demand zone within Reculver. Once again, because of this store's size, the expenditure inflow makes up only a small proportion of store revenue (around 3% in the peak season). This may sound insignificant, yet this simple example clearly highlights the potential to use the model to explore characteristics of the demand side as well as the supply side. Such observations could be used to support store planning applications, demonstrating that new foodstore provision enhances facilities available for both residents and visitors in tourist resorts.

This scenario highlights that the SIM and demand side estimates can be used to evaluate demand side changes, accounting fully for the seasonal and spatial characteristics of visitor demand. Section 8.6.2 considers an alternative demand side scenario, focusing instead on changes to the seasonal pattern of demand driven by a change of utilisation patterns, rather than additional accommodation provision.

8.6.2 Year-round occupancy of visitor accommodation

In spite of the increased demand for self-catering accommodation noted above, Thomason and Keeling (2012) identify that there has been a decline in the supply of static caravans as visitor accommodation within Kent. In part this is driven by changing tastes but also results from the fact that this form of accommodation has come under pressure for alternative use as residential units. Many static caravans sited on registered holiday parks are owner-occupied by a private owner, renting a plot of land from the park operator and paying ground rent and a charge for services. Beatty *et al.* (2012) note that this form of accommodation, particularly in seaside locations, are an increasingly popular choice of year round residential accommodation. In a comprehensive study of owner-occupied static caravans in coastal destinations they found that substantial numbers of people live in statics for a considerable portion of the year. However, due to planning conditions, they note that most sites close for part of the winter period and as such many instances of these units being owner-occupied go unrecorded in official statistics such as council tax records and in the census, local population statistics and the electoral roll.

Potentially, therefore, these forms of accommodation may not be fully-incorporated within traditional estimates of local level residential grocery demand, since this form of dwelling is not commonly considered to represent a residential unit. Where they are occupied as visitor accommodation, static caravans tend to be highly seasonal in nature and have been reflected as such within the demand estimation carried out in section 8.3.1. Where some of these units may instead be used as a residential dwelling, it is likely that demand associated with them is underestimated, particularly in the low season. Since these units tend to be clustered heavily into large holiday parks, this may have a considerable impact on local-level seasonal expenditure estimation. An interesting question thus arises: how would the seasonal pattern of demand change if a proportion of the static caravan units were instead considered to be owner-occupied all year round? This question is considered within this scenario, with reference to a large holiday park in the Shepway District.

The accommodation audit (see section 8.3.1.1) records a total supply of almost 2,500 static caravans as visitor accommodation within the Shepway district, representing around 40% of the total supply across the study area. The largest park (by number of units) in the Shepway District is the Romney Sands Holiday Village near New Romney (see Figure 8.1 and Figure 8.2), with 480 static units. This park has a 45 week operating season for owner-occupiers (1 Mar – 15 Jan). Aside from this closure period, the site advertises facilities for owner-occupiers all year-round, suggesting that a number of these units tend to be occupied for the full park season, thus generating local demand for groceries for up to 45 weeks of the year. The expenditure modelling has identified that this park generates considerable expenditure during the peak-season (with this OA generating over £35,000 per week visitor expenditure in August), but is thought to exhibit very low occupancy rates (and thus generate

little grocery demand) in the low season, falling to less than £1,000 per week visitor expenditure in January.

The 2011 census provides some indication of the rates of owner-occupancy of static caravans. It records 2,853 households living in a dwelling classified as a 'Caravan or other mobile or temporary structure' within the East Kent study districts[42]. The Kent accommodation audit identified a total supply of 6,799 statics within the study area, suggesting that 42% of the supply of statics may represent a residential dwelling. However, the rate of owner-occupancy appears to vary considerably by district. Based on the accommodation audit and 2011 census data, 72% of statics in Thanet are recorded as owner-occupied, yet the corresponding proportion of the Shepway District is just 11%. When used in conjunction with the SIM, the visitor and residential expenditure estimates provide an opportunity to simulate the impacts of changes in the proportion of accommodation units that are actually occupied as residential dwellings. This will be considered in relation to the Romney Sands Holiday Village, with the impact at a store-level considered using the nearby Sainsbury's store in New Romney.

Figure 8.9 illustrates the available expenditure (considering both residential and visitor demand) originating from the OA which contains the Romney Sands Holiday Village. The available expenditure is shown across 12 months (using 2011 data) and under four scenarios. In the first scenario, all 480 static caravan units on the park are considered to represent visitor accommodation and corresponding occupancy and expenditure rates are applied. Under three further scenarios, 11%, 42% and finally 72% of these units are instead thought to represent residential dwellings, with appropriate expenditure rates applied. These proportions are based on current inferences about owner-occupancy of static caravan units taken from census data (see Table 8.12). In all cases, the 7 week closure of the site in late January and February has been taken into account.

It is apparent from Figure 8.9 and Table 8.12 that the use of a proportion of the accommodation stock as residential units has little impact on peak season demand, with total available expenditure from this demand zone exceeding £50,000 per week under all four scenarios. The impact is apparent, however, in the low season, where residential use of these units considerably boosts demand in this area. For example, in March, if 42% of the available accommodation units are instead thought to represent residential dwellings, overall available expenditure doubles (an £18,000 increase). If levels of owner-occupancy reach the rates inferred for the neighbouring Thanet district (72%), then average weekly expenditure increases by over 50%, even after accounting for site closures in January and February. This represents a clear cluster of expenditure and retailers in close proximity to sites such as this

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[42] Table KS401EW (Dwellings, household spaces and accommodation type, local authorities in England and Wales)

may wish to consider the impact of demand associated with a large number of owner-occupiers using these units all year round.

The closest supermarket to the Romney Sands Holiday Village is the 11,500 Sq Ft Sainsbury's store in New Romney, 2.8 miles away. This small store is modelled to attract around a third of its revenue from visitors in August, including over £29,000 from the demand zone incorporating Romney Sands Holiday Village (representing a market share of over 50%). Modelled results identify that this OA accounts for up to 8% of the New Romney store inflow, and as such, fluctuations in demand within this OA may have a clear impact on store performance. Figure 8.10 illustrates the New Romney store inflow from this OA by month (2011) under the current scenario (all 480 units represent visitor accommodation) and under the most extreme scenario, whereby 72% of these units are under year round occupancy (excluding site closure). The impact of residential occupancy on overall seasonal revenue fluctuations at a store-level is clearly apparent, with 72% residential occupancy giving rise to far less pronounced seasonal demand uplift, considerably boosting demand in the low season.
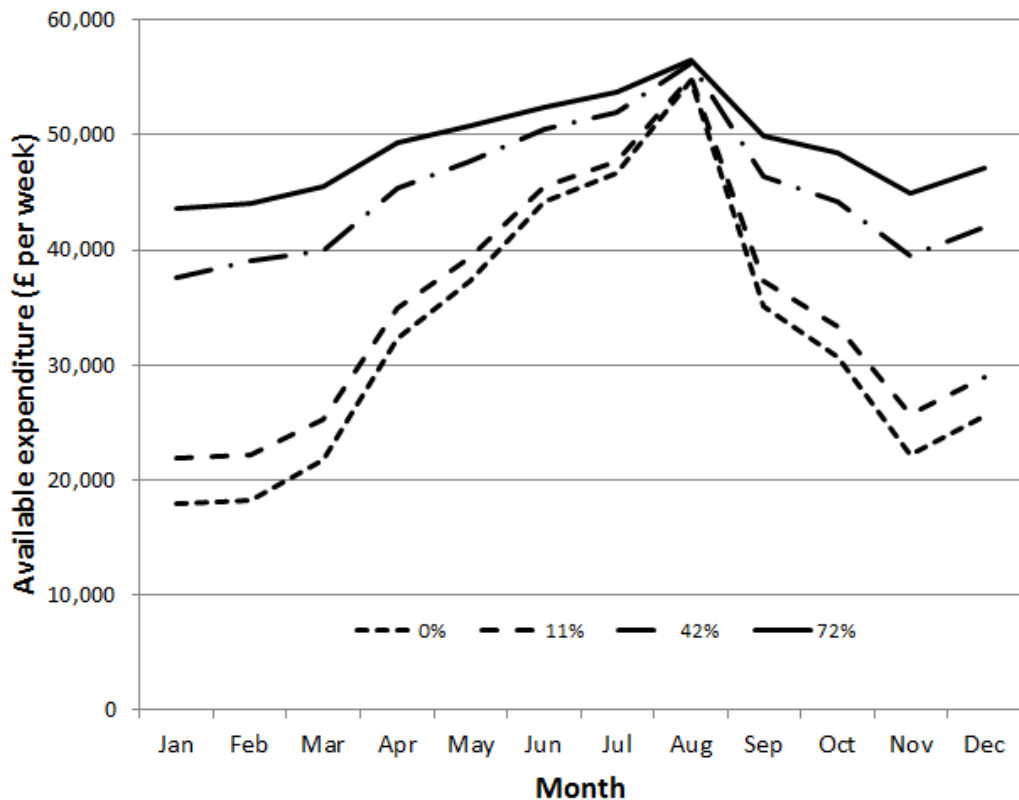
Figure 8.9 - Available expenditure originating from the Romney Sands OA following reallocation of accommodation stock to residential dwellings

Four scenarios are shown representing the proportion of the accommodation stock transferred to residential dwellings, ranging from 0% (all units classified as visitor accommodation) through to 72% of units reclassified as residential dwellings for the modelling process. Available expenditure within OA 29ULGS0007.

This section clearly highlights the impact that residential occupancy of accommodation units may have on seasonal fluctuations in local-level demand. Figure 8.10 notes that residential use of units on one large holiday park can generate a considerable spatial cluster of demand which exhibits less seasonal fluctuation in terms of available expenditure. In particular, low-season demand receives a considerable boost, with store-level impacts at a nearby supermarket likely to be experienced. Whilst this particular context is in itself interesting, it serves to highlight more generically the capacity within the model to consider the impact of demand side changes on seasonal demand and subsequent store-level trading characteristics.

Table 8.12 - Romney Sands available grocery spend under four scenarios

Scenario	Explanation	52 week Average Available Expenditure	Average Weekly Expenditure (August)
All units visitor accommodation	Based on the accommodation database and modelled expenditure.	£32,240	£54,794
11% of units residential	Inferred as the current proportion of owner-occupied statics in the Shepway district	£34,778	£55,063
42% of units residential	Inferred as the current proportion of owner-occupied statics across the study area	£45,020	£56,139
72% of units residential	Inferred as the current proportion of owner-occupied statics in the nearby Thanet District	£48,844	£56,554

These small-scale demand side changes may often be overlooked within revenue estimation, yet this section demonstrates that the model offers considerable potential to simulate these forms of demand side changes in order to evaluate the impact on local service provision, as considered further in section 8.7
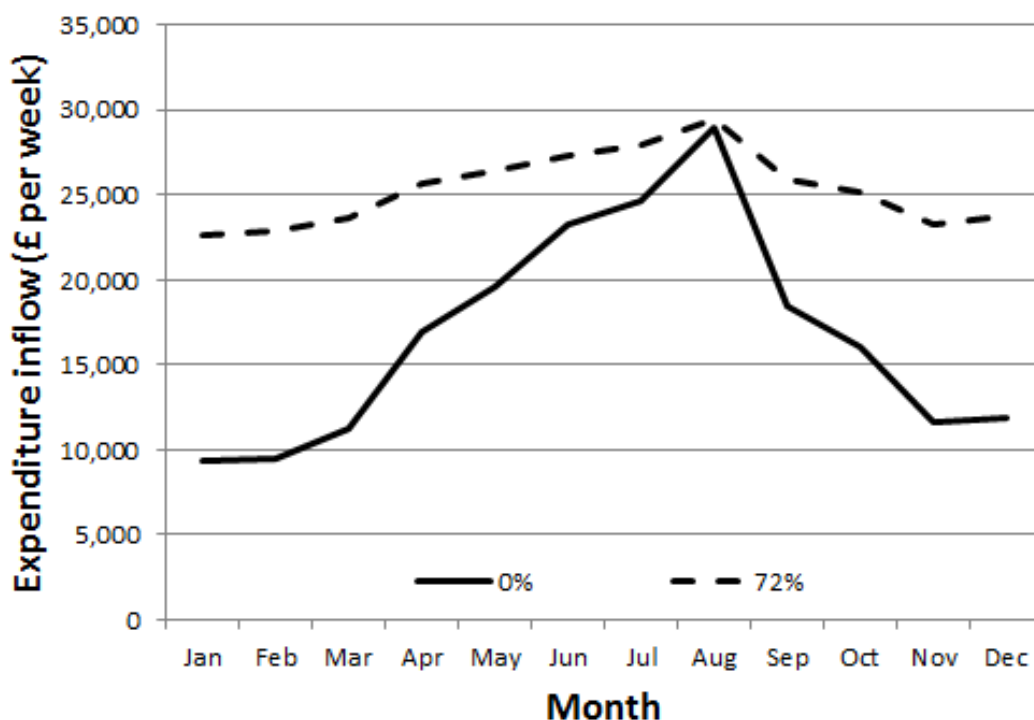
Figure 8.10 - Expenditure inflow to Sainsbury's New Romney store from the Romney Sands OA following reallocation of accommodation stock to residential dwellings

> Two scenarios are shown representing the proportion of the accommodation stock transferred to residential dwellings, ranging from 0% (all units classified as visitor accommodation) through to 72% of units reclassified as residential dwellings for the modelling process. Available expenditure within OA 29ULGS0007.

8.7 Conclusions

In common with Chapter 7, the analysis presented within this chapter sought to demonstrate that the modelling approach developed throughout this thesis can be used to estimate store-level revenue in tourist areas with greater accuracy. The results presented in section 8.5 undoubtedly identify that this has been achieved. In common with the results obtained for Cornwall, it has been possible to estimate seasonal store-level revenue fluctuations to a very acceptable level of accuracy. A total of eight Sainsbury's stores were considered, encompassing a range of different store and destination types. In 75% of cases, overall revenue estimation to within 5% of reality has been achieved. Clear supply side factors which are tricky to model account for relative under or over-estimation at the remaining two stores. Industry and academic evidence presented throughout this thesis suggests that store-level revenue prediction to within 5% of observed values represents very effective application of a SIM.

Chapter 6 acknowledged that estimating seasonal revenue fluctuations is tricky due to the huge range of short-term factors affecting actual store-level demand which cannot realistically be incorporated into a predictive model of this type. Nonetheless, seasonal

(monthly) revenue fluctuations have been consistently predicted to within 10% of reality, and often to within 5%, for six study stores in Kent based on 2011 data. This is encouraging and suggests that across both Cornwall and Kent, seasonal demand estimates, used in conjunction with a disaggregate SIM, are a very powerful tool for retail location planning. This argument is considered further in Chapter 9.

This chapter also sought to demonstrate that seasonal and spatial variations in grocery demand are evident in a destination such as East Kent, where overall visitor numbers and seasonal sales uplift may be less pronounced. Whilst Kent lacks large scale holiday parks to the same extent as Cornwall, the expenditure estimation has revealed that considerable clusters of visitor induced demand do still exist, particularly driven by those visitors using commercial self-catered accommodation. The study area incorporated the popular city of Canterbury and the port town of Dover, revealing the importance of these destinations in driving visitor numbers and associated spend, alongside more traditional coastal resorts.

The expenditure estimation process carried out in section 8.3 also suggested that, where suitable local-level data collection exists, considerable pre-processing of input data (such as the accommodation stock) is not required. This realisation makes this form of expenditure modelling a more realistic prospect for major retailers such as Sainsbury's and suggests that existing databases of visitor accommodation, as held by some destination management organisations, is sufficient for robust expenditure estimation. From the perspective of under-resourced location planning teams, the expenditure estimation carried out within this chapter also suggests, in common with Chapter 5, that a considerable proportion of the seasonal visitor expenditure uplift is attributable to visitors using commercial self-catered accommodation, particularly within the peak season. For an area such as Cornwall this was unsurprising, given the high propensity for overnight visits. However, Kent experiences a higher proportion of day-trip visitors than Cornwall, and VFR tourism also accounts for a considerable proportion of visits. As such, and particularly in the low season, expenditure associated with these forms of tourism accounts for a sizeable share of non-residential expenditure, and should be considered within the expenditure estimation process.

The expenditure estimation and SIM together form a powerful tool to explore the impact of both demand and supply side changes. Further to the supply side analysis carried out in Chapter 7, section 8.6 clearly demonstrates the model's utility in simulating the impact of demand side changes on spatial and temporal patterns of available grocery expenditure and their supply side impacts. Although the focus of this thesis has primarily concerned the use of the model to explore supply side changes (such as new store development), this chapter identifies the flexibility of the model to handle demand side changes which may be of interest to destination management organisations such as VisitKent or other local service providers.

In summary, this chapter complements the modelling presented in Chapters 5 – 7, demonstrating unequivocally that the modelled accuracy of store-level revenue predictions achieved in Cornwall can also be achieved in an additional and un-related study area. This observation suggests that, with suitable application of local seasonal utilisation and expenditure rates, this approach could be applied to any number of tourist areas in order to estimate grocery demand, or other forms of expenditure or service demand associated with visitors. These ideas are considered more fully in Chapter 9.

Chapter 9: Discussion, conclusions and future research agenda

9.1   Research outputs and achievements

This thesis has sought to develop a robust methodology to account for seasonal visitor induced demand uplift within location-based modelling for use in retail location planning. Retail location planning in many large grocery firms relies on the spatial interaction model (SIM) to evaluate the trading potential of new sites (Birkin *et al.*, 2010b). However, there has traditionally been an inherent weakness in the handling of highly seasonal visitor demand (as driven by tourism) within the SIM, as addressed throughout this thesis. The research reported within this thesis has successfully addressed the key aims set out in the introduction: to develop a methodology to estimate small-area grocery demand in highly seasonal tourist resorts and to develop and calibrate a SIM to generate robust store revenue predictions for store investments in tourist areas. These aims sought to enhance the predictive capacity of retailers' location-based decision making in tourist areas.

Two key outputs originate from this thesis: a methodology to estimate spatial and temporal patterns of small-area grocery demand in tourist areas and a SIM which can be used to predict consumer flows, revenue and associated market share for proposed stores in tourist resorts. Both have been developed with reference to the tourist sector and grocery industry in Cornwall and also in East Kent, with a particular focus on highly seasonal coastal resorts. The demand side estimates have been produced at an OA level and represent a major advance in the understanding of seasonal and spatial patterns of small-area non-residential populations and their associated expenditure, as noted fully in section 9.2. The thesis clearly outlines the methodology employed to produce these seasonal expenditure estimates, critiquing the data sources used. Section 9.3 comments fully on the propensity for location planning teams to produce similar demand-side estimates in-house.

As noted extensively throughout this thesis, the SIM is an important tool for store revenue prediction. Sophisticated SIM have been developed to estimate store trading potential, fuelled by increasing volumes of consumer data. The model produced within this thesis, in conjunction with the seasonal demand side estimates, can be used to predict store revenue in tourist areas, accounting fully for seasonal sales variations driven by visitor expenditure. The model is disaggregated on the demand and supply sides and is a powerful tool for modelling seasonal and spatial patterns of consumer flows, store revenue and market shares. Working in collaboration with the location planning team at Sainsbury's has provided rare access to store and consumer level data. These have been a valuable tool for model calibration and allow the ability of the model (in generating robust revenue predictions) to be assessed.

Section 9.2 begins with a summary of the research findings, organised around the key aims and objectives.

9.2 Summary and critique of research findings

A series of objectives were outlined in Chapter 1 and have been addressed systematically throughout this thesis. This section seeks to draw a summary and critique, and is organised around the research aims, with the key outputs and findings summarised. The aims were developed in consultation with Sainsbury's and reflect their identified weaknesses in the location planning process for new store development in highly seasonal tourist resorts. The nature of the collaboration itself (and full justification for its applied focus) was outlined in Chapter 1. In addressing each aim, the methodologies, data sources and approaches used are also critiqued.

9.2.1 Aim 1: To review the existing literature and available industry data to identify the impact of visitor expenditure on store-level grocery demand

This first key aim recognises that an inherent demand side weakness exists in the handling of visitor demand within location-based modelling. Chapter 2 introduced the sector fully, noting contemporary growth opportunities and the impact of changing consumer demand and regulation on the supply side. The discussion focussed primarily on the importance of location and the role of location planning as a strategic and operational function within grocery retailers. Having outlined the growth of location planning teams within retailers such as Sainsbury's, attention turned to the modelling employed in order to assess the trading potential of proposed stores or network investments. Drawing on academic and industry literature, the role of the SIM as a tool for revenue prediction was noted, exploring fully the theory of spatial interaction and development of the classic production-constrained entropy model for retail applications. It was noted that this form of modelling has become an important and increasingly accurate tool to generate store-level revenue predictions in advance of investment.

Store revenue is generally driven by expenditure originating from residential households. A comprehensive understanding of this form of demand exists via the census, neighbourhood based geodemographics and consumer loyalty card data. As a result, retailers are typically able to generate robust estimations of the small-area spatial patterns of demand and employ SIM to link the supply and demand sides, predict consumer flows and generate store revenue predictions with some accuracy (Birkin *et al.*, 2002). However, Chapter 2 noted that in some areas, non-residential populations, in the form of students, commuters or tourists, drive additional expenditure and store-level revenue uplift. Whilst retailers have begun to address some forms of non-residential demand (such as workplace populations) within their

modelling, handling visitor demand remains complex. Little is known about the driving factors, and the highly seasonal nature of this form of demand means that the store-level impact fluctuates considerably at different times of the year. Retailers such as Sainsbury's therefore note that their revenue predictions underestimate store revenue for many stores located in coastal resorts or similar highly seasonal areas (Feltham and Davis, 2010).

Modelling this form of demand is an under-researched area within the literature, a gap which Chapters 3 and 4 identified and attempted to address, exploring the seasonal and spatial nature of visitor demand further. Whilst this thesis addresses this issue from a location-based modelling perspective, Chapter 3 situated the research within the established literature from the tourist sector. It was noted that visitor expenditure is an important driver of highly seasonal demand within tourist destinations and resorts. Identifying visitor demand from the supply side is complex and, as such, the nature and impact of visitor expenditure at a local level is commonly inferred based on demand side indicators (Buccellato *et al.*, 2010b). A series of national sample surveys were introduced and, in conjunction with economic impact models, this form of survey data are often used to determine the economic impact of tourism at sub-regional levels. Nevertheless, the overarching conclusion was that very little is known about the impact of visitor expenditure on individual sectors or services within resorts and similar destinations. In spite of the spatial clusters of visitors usually found around key tourist resorts and destinations, visitor populations are commonly omitted from small area population estimates. Little is known about actual visitor numbers, or their seasonal and spatial distribution at a sub-district level, and insight into this form of demand, and its impact on the grocery sector is limited to small-scale local survey data and isolated studies.

Consequently, Chapter 3 noted that very little insight exists into the spatial or seasonal patterns of visitor grocery expenditure at the local level, yet presented a range of evidence outlining the importance of visitors in driving this form of demand. In particular, and in common with the economic impact models reviewed, it is clear that the overall volume of visitors, and their associated trip purpose and accommodation used (where appropriate), drive grocery demand at the local level. Noting that no suitable demand side expenditure estimates exist, Chapter 3 recognised that this thesis needed to estimate seasonal grocery demand at the small-area level. Seasonal and spatial patterns inherent in domestic tourism were thus outlined, and the key forms of visitor, trip purpose and accommodation were introduced, drawing on limited academic and tourist sector literature to identify key data sources and studies that can be used to develop a demand side understanding of visitor grocery expenditure.

With this thesis also benefitting from access to store and loyalty card data from selected Sainsbury's stores, Chapter 4 offered a unique perspective on the nature of seasonal demand uplift at a store-level. Chapter 4 noted that Cornwall is a popular destination for highly

seasonal domestic tourism, with a high propensity for visitors to use self-catering accommodation. The importance of self-catering accommodation (which primarily attracts domestic holidaymakers) in driving grocery demand was noted in Chapter 3. With reference to trading data for four stores, Chapter 4 outlined the highly seasonal nature of trade at two stores located in the popular resorts of Newquay and Bude. The considerable sales uplift and highly seasonal nature of demand at these stores was explored. The key insights were, however, drawn from analysis of loyalty card data at the individual consumer level using Nectar card data. Categorising loyalty card trade by consumers' spatial origin allowed the identification of those transactions inferred to be attributable to visitors. Comparisons were drawn between the characteristics of visitor and local residents' expenditure, and visitor spend within the destination was compared to their regular home spend. The analysis identified that the nature of visitor grocery expenditure is complex, with inherent differences in the geodemographic characteristics and expenditure profiles of visitors and local residents, which vary on a store-by-store basis.

Based on the evidence presented in Chapters 2-4, it was strongly concluded that existing approaches to estimate visitor spend at the store-level (commonly based on some form of expenditure up-scaling) simply cannot account for the seasonal and spatial characteristics inherent in visitor demand, or the different characteristics between visitor and local residents. As such, the analysis presented in Chapter 4, coupled with the established literature, suggests that a series of small-area visitor demand layers must be produced, determining the available grocery expenditure, for use as an input to SIM. These are addressed within section 9.2.2

9.2.2 Aim 2: To develop a methodology to estimate small-area grocery demand in highly seasonal tourist (coastal) resorts, accounting for the spatial and temporal (seasonal) variations driven by visitor expenditure.

Small area seasonal and spatial demand estimates were produced in Chapter 5 for the County of Cornwall at a Census Output Area (OA) level and are based on the insight into the grocery consumption habits associated with different types of visitor, visit or accommodation, as reviewed in Chapter 3. Chapter 5 systematically and comprehensively outlined the production of these demand layers, noting in full detail the data sources used (accommodation stock, occupancy/utilisation and expenditure rates). The visitor demand layers were produced for 13 time periods (12 different months of the year and a 52 week average) and, on an OA-by-OA basis, provide an estimate of the average weekly food and drink spend attributable to all forms of visitor. Visitor expenditure incorporates induced spend associated with those hosting visiting friends, relatives or paying guests. Coupled with residential demand estimates (which account for a seasonal outflow of residential households holidaying elsewhere, and adjustments to account for workplace populations), a series of

seasonal demand layers have been produced. Similar estimates were produced in Chapter 8 for four districts in East Kent.

These small-area seasonal and spatial demand estimates address a key aim of this thesis and represent a major output; they were also used as an input to the spatial modelling carried out in Chapters 6 and 7. Since no comparable small-area estimates of visitor numbers, their seasonal and spatial distribution or associated expenditure are available, it is very difficult to validate or assess the accuracy of these visitor demand layers as an individual output from the thesis. Their accuracy is assessed in terms of their ability to generate robust revenue predictions when used in conjunction with a SIM, but the overall accuracy of those predictions is based on the calibration of the model too, and not solely on the demand estimates. As such, the demand estimates can only be critiqued against the input data and methodology used to create them.

Since no established methodology exists for estimating visitor numbers or their associated grocery spend (at any spatial scale), the approach used in generating small-area expenditure estimates here was developed with reference to a number of approaches employed within the tourist sector. In its simplest form, the approach involved estimating the volume of visitors at any given time of year, then applying appropriate expenditure rates. Based on established industry approaches (e.g. STEAM and Cambridge Model), the accommodation stock was thought to be a key driver of visitor numbers, also determining their spatial distribution. The use of occupancy rates allowed the seasonal distribution of these visits to be incorporated, followed by surveyed expenditure rates from the literature. Whilst there were a number of issues in identifying the underlying accommodation stock, occupancy rates and associated expenditure, it is thought that this approach accounts for the key drivers of expenditure associated with visitors using these forms of accommodation.

It is harder, however, to incorporate other forms of visitor demand within the small-area expenditure estimates. For example, rates of second home ownership, utilisation or associated expenditure were difficult to identify, and no suitable data sources exist to identify induced visitor expenditure in grocery stores by the operators of small accommodation establishments. Furthermore, seasonal and small-area spatial patterns of day visitors, or insights, into their associated grocery expenditure, are very limited. Chapters 5 and 8 identified that expenditure associated with visitors using self-catered accommodation accounts for the greatest proportion of non-residential demand in Cornwall and Kent, and the data sources to identify the seasonal and spatial distribution of these visits (accommodation stock and occupancy) are generally readily available. However, the importance of day visitors is also noted in both study areas, and it is recognised that the data sources and associated expenditure estimates applied here are limited. Nevertheless, the real success of

the demand side expenditure estimates are in their ability to predict store revenue to an acceptable level of accuracy when used in conjunction with a SIM, explored in section 9.2.3.

9.2.3 Aim 3: To develop and calibrate a SIM to handle seasonal grocery demand within tourist areas, demonstrating that it can generate robust revenue predictions as a tool for evaluating proposed supply or demand side changes.

Utilising the demand estimates produced in Chapters 5 and 8, this aim sought to demonstrate that, when used in conjunction with a SIM, these demand layers can generate robust revenue predictions (and address the full range of demand and supply side questions commonly considered by location planning teams). As such, Chapters 6 - 8 sought to develop and calibrate a SIM capable of handling seasonal demand estimates and to demonstrate, via a series of scenarios, that the SIM and demand side estimates can be used for store location planning in a number of tourist resorts and under a series of supply and demand side scenarios. Chapter 6 fully documented the development, calibration and validation of the SIM in Cornwall, with a similar discussion for Kent in Chapter 8.

The SIM, developed from scratch for this thesis, has been disaggregated on both the demand and supply side. This reflects the input data, with visitor and residential demand fed into the model as separate layers. A series of seasonal demand layers are available, representing different times during the tourist season. Handling each form of demand separately allowed independent model parameters to be set. For example, on the demand side, a series of different beta values were utilised for residential households in order to represent the relative propensity, ability or willingness of different households to travel a greater distance to a store of choice, based on their income. Disaggregation on the supply side also means that the relative attractiveness of different stores (based on their brand) could be incorporated, with evidence presented in Chapter 6 suggesting that the strength of different brands or fascias can be considered relative to household type, with consumers categorised based on the Output Area Classification.

Model disaggregation ensures that the model replicates observed consumer behaviour as closely as possible, taking account of important consumer characteristics (such as income, importance of distance and brand preference) on their grocery purchasing habits. Likewise, the use of travel time data ensures that travel 'cost' (recognised within the SIM as a key influence on consumer expenditure flows) reflects industry approaches in the development and operation of these models. The availability of consumer flow data from the Nectar loyalty card scheme is invaluable for model calibration and, as such, this thesis represents one of very few examples in the academic literature of a SIM that has been calibrated with reference to empirical data from a major retailer. Consumer level flows (52 week average) from the loyalty card data allowed the modelled flows of residential (household) demand to be calibrated against observed data.

Using average trip distance (ATD), the coefficient of determination (R^2) and the standardised root mean square error (SRMSE), Chapters 6 and 8 demonstrated that the SIM, applied in both Cornwall and East Kent, can replicate observed 52 week average flows (for residential demand) to a very impressive level of accuracy. Unfortunately, however, suitable volumes of consumer level flow data are not available on a week-by-week basis to calibrate the seasonal component of these flows and no flow data is available for visitors. The lack of suitable flow data to calibrate the SIM against observed flows of visitor expenditure (from their origin within the destination, such as their accommodation) represents a major challenge for this form of work. Since no suitable flow data are available, the accuracy of the visitor demand estimates and subsequent modelled flows can only be assessed with reference to the model's ability to generate robust seasonal revenue predictions.

With access to store-level revenue estimates on a week-by-week basis, the models ability to predict store revenue at different times of year was assessed in Chapters 6 and 8. Running the model on a month-by-month basis (using the monthly seasonal visitor and residential demand layers) allowed average weekly revenue (originating from both visitors and local residents) to be estimated on a month-by-month basis. Comparison of observed and predicted revenue for a total of 12 Sainsbury's stores (across both study areas) suggested that the model is consistently able to predict revenue to within 10% of reality, after incorporating visitor demand, and often to within 5% (a very encouraging model performance). Chapter 6 identified some of the limitations in considering revenue at different times of the year, recognising in particular the impact of short term local factors (such as roadworks, in-store promotions, competitor activity, local events etc.) in influencing week-by-week store revenue. At the spatial scale modelled here, it is impossible and unrealistic to incorporate all factors that could affect store performance within such a model. Due to their highly seasonal nature, these stores must represent some of the most complex to model, and the model's ability to do so to within 10% of observed revenue is very encouraging.

Chapters 7 and 8 demonstrated that the seasonal demand estimates applied within a disaggregate SIM can be used to address a number of typical supply and demand side scenarios that would be considered by location planning teams. These scenarios (which were documented within their respective Chapters) identify the range of insights that this form of modelling can generate. On the supply side, the scenarios chosen (all within coastal tourist resorts) explored the use of SIM and seasonal demand estimates to assess the trading potential of individual stores. These scenarios demonstrated that the model can be used to estimate store revenue and to identify the impact of supply side changes on consumer flows, store and retailer market shares and network performance. The demand side scenarios, again within coastal tourist destinations, highlighted that the model and demand side estimates have the versatility to handle changes in the overall demand, or in its seasonal and spatial patterns.

The discussions within Chapters 6 - 8 clearly highlighted the model's utility and demonstrate its capability to model seasonal demand fluctuations at a store-level, consistently predicting store revenue with accuracy in tourist areas. Subject to data availability, it would be entirely feasible to update demand side estimates and model seasonal visitor demand for any specified year. Based on assumptions about future visitor numbers, their spatial distribution and future spend, it would also be feasible to forecast store revenue under a number of assumptions reflecting changes in holiday making behaviours, institutional calendars or destination capacity.

Having summarised and critiqued the major insight, analysis and outputs originating from this thesis, section 9.3 reflects the applied nature of this research and identifies its potential contribution within industry. Section 9.3 considers the ability of location planning teams to develop similar demand side estimates and carry out similar modelling using their in-house resources.

9.3   Recommendations for application within location planning

Chapter 1 outlined the applied nature of this research, recognising that it sought to address a demand side weakness in the handling of visitor demand within spatial modelling. The involvement of Sainsbury's as a CASE award partner reflects an industry-wide interest in understanding more about the impact of non-residential populations at a store-level. The ultimate aim for Sainsbury's is to be able to develop similar seasonal and spatial demand estimates for all tourist areas, such that proposed store investments could be assessed on their full trading potential, incorporating all forms of relevant visitor demand uplift and seasonal demand fluctuations. Based on the work reported within this thesis, and recognising the limited resources available to many location planning teams, a number of key recommendations are made should retailers wish to incorporate seasonal visitor demand within their location-based decision making. The recommendations and applicability of the approach developed within this thesis are briefly discussed below.

In developing these estimates, the thesis benefitted greatly from access to data held by two local or regional tourist organisations, as documented fully throughout the preceding Chapters. South West Tourism (SWT) and VisitKent both provided full access to their databases of visitor accommodation, both of which were the most complete listings available. In the case of Cornwall, considerable data cleansing and updating was required before the database could be used for analysis, including updating missing or miscategorised units, adding missing postcodes and amending incomplete details about the number of units, bedrooms and bedspaces through web searches, contact with visitor/tourist information centres, agencies and accommodation operators. This represents a considerable investment in time, effort and resources and it is recognised that it is unrealistic for even the largest location planning teams to undertake this sort of task for large areas.

In Chapter 8, a similar accommodation audit for East Kent was used in an almost completely 'off the shelf' format, with very limited data cleansing carried out. The robust revenue predictions that resulted from the East Kent demand layers suggest that, whilst not perfect, similar local-level accommodation audits could be applied elsewhere with little pre-processing. It is recognised that accommodation audits and databases will never be able to incorporate all possible visitor accommodation, and will be outdated almost as soon as they are complete (due to the fragmented nature of this sector and ease of entry and exit (Johns and Lynch, 2007)). Nevertheless, given the importance of self-catering accommodation in driving visitor grocery spend, it is strongly recommended that location planners ensure that all large accommodation sites (such as holiday parks or campsites) are incorporated within demand side estimates and that they attempt, where possible, to update capacity and operating seasons, especially when these large sites are in close proximity to proposed stores.

Whilst some form of accommodation audit will be held by local authorities and destination management organisations (generally as an input to economic impact models such as the Cambridge Model), getting hold of this data may not be straightforward. Gaining access to the SWT and VisitKent databases took considerable time and effort and relied upon contact made at industry events and considerable follow up and face-to-face meetings before access was granted. Obtaining subsequent updates would have required further follow up and often relies on the willingness of individual members of staff, with contact broken if that member of staff moves onto another organisation. Retailers may, however, be able to gain access to these datasets via agreement with local councils, especially where they are proposing new retail facilities and associated services in tourist areas, attracting support from local authorities, who may then be willing to release such data.

Alternatively, there may be scope for retail consultancies to produce similar small-area seasonal demand estimates, using a methodology similar to that which has been outlined in Chapter 5. The value that these demand side estimates may bring to the assessment of store trading potential has been demonstrated throughout this thesis, and thus there may be sufficient demand for some form of seasonal grocery demand estimates to be generated as a commercial product. One or more retail consultancies may seek to generate such layers, for purchase by major retailers and for use within their modelling framework. Whilst the development of the initial layers would be a major undertaking, the impact on location-based decision making may be pronounced. Considerable effort would need to be invested in maintaining those demand layers. They would need updating frequently to reflect changes in the accommodation supply or reflect key drivers of seasonal variations. This may be beyond the scope of under-resourced location planning teams (in terms of the workload required), but may be attractive to a retail consultancy for application across the industry.

If retailers were to attempt to replicate such layers in-house, it is recommended that one of two approaches is used, depending on the intended application. Both approaches draw on the modelling developed and applied within this thesis. The first approach would be most

applicable where a retailer wishes to generate seasonal demand layers for a large spatial extent (e.g the County of Cornwall or South West England). Here it is recommended that the demand side estimates just seek to incorporate commercial self-catered accommodation, focussing mainly on the large holiday parks and campsites, applying regional or county-wide occupancy rates. It is also recommended that overall numbers and a broad spatial distribution of day visitors are incorporated (where available). In conjunction with the expenditure rates applied within this thesis, this approach would account for the key drivers of visitor grocery demand (visitors using self-catered accommodation and large volumes of day visitors) and provide a crude but realistic indication of the magnitude, spatial and seasonal distribution of visitor expenditure. Such an approach could be used to obtain an idea of the likely impact of visitor demand on store revenue when developing network plans, investment 'wish lists' or screening a number of possible sites for new store investment ahead of a more detailed assessment.

The second approach applies where a specific site has been chosen and analysts wish to explore, in detail, the trading potential of a new store investment. Here it is recommended that the full approach outlined in Chapters 5 and 8 is applied, yet the spatial scale over which the demand layers are built could be far more restricted. Chapers 5 and 8 sought to generate robust and detailed revenue predictions for multiple stores on a county-wide or multiple-district basis. The spatial scale at which this thesis has been carried out far exceeds the spatial scale that would be modelled in individual store-level scenarios. When assessing individual store proposals, a 15 minute (urban or suburban) or 30 minute (rural) drive time may be an appropriate threshold, allowing the more detailed and resource intensive incorporation of spend associated with second home ownership, VFR, and spend by accommodation operators. At this spatial scale it may be realistic to carry out surveys to ascertain visitor expenditure and visitor flow data for use within the framework developed here. The impact of these forms of expenditure on seasonal demand uplift have been noted to be less pronounced, and so their exclusion, where suitable data cannot be sourced, is unlikely to impact noticeably on the accuracy of revenue predictions.

The recommendations noted above are based on the demand side seasonal demand layers, since these are the key output of interest to Sainsbury's as collaborating partner. There are also a number of improvements that could be made to the handling of this form of demand within a SIM if suitable data were available. The improvements suggested would be of considerable interest to retail location planning teams, and these teams are best-placed to collect the data that would be required. Given that the ESRC has recognised the importance of the data held by the retail sector, it is envisaged that further model development could represent a follow on study, conducted with the support of Sainsbury's or an interested retailer with access to similar consumer data.

Section 9.4 identifies some of the developments that could be made to the SIM itself (and the consumer data that would be required), along with broader follow up work that could

originate from this research, of interest to either the academic community, industry practitioners or both.

9.4   Further development and future research

The research reported within this thesis has specifically considered a demand side weakness in the handling of visitor demand within spatial interaction modelling for store location planning. Nevertheless, reference to the academic literature (Chapter 3) clearly identified that the development of small area visitor demand estimates goes some way to address a far broader weakness in the understanding of seasonal, small-area non-residential populations. There is potential for further development of the model and demand estimates for use within retail location planning, and for broader application in understanding small-area populations. Consequently, there are a considerable range of future research avenues along which this thesis could be developed further. It is beyond the scope of this section to address all possible developments and further research and, as such, the comments made below are naturally selective. They attempt to represent the diverse range of further research that could be completed and are not attempting to be an exhaustive list. Instead they represent the authors' judgement of five key areas of further research that could be explored.

The first suggestion relates to the development of the SIM itself, enabling its full potential in handing visitor demand to be utilised. The model calibration carried out in Chapters 6 and 8 is limited by the lack of suitable flow data in order to calibrate the visitor demand component of the model. As such, observed flows from the Nectar scheme were used to identify expenditure flows originating from residential households within the study area. Whilst visitors themselves can be identified (since their loyalty card is registered to a postcode outside the study area), their demand origin within the study area is unknown. As such, visitor demand is identifiable at the store-level, but the local origin of those flows is unknown. Consequently, visitor demand has been modelled at an OA level, but the modelled flows of visitor demand from each OA to individual stores cannot be calibrated against observed data. The model thus relies on known characteristics of residential demand flows, and assumes that visitor demand is driven by the same underlying factors. The presence of suitable flow data for visitors would allow model parameters (alpha and beta) to be set independently for visitor demand. For example, the impact of distance or travel time may be less pronounced for visitors, or visitors may display different brand preferences - perhaps trading up to higher end retailers whilst away from home. Suitable flow data would enable these factors to be identified and incorporated within model calibration. Retailers do not currently hold any data suitable for this form of collaboration. However, in conjunction with a retailer, it would be possible to collect this information (via in-store surveys identifying visitors and recording their origin within the destination, such as the location of their accommodation). Data of this form would allow the disaggregate nature of the model to operate to its full potential.

Second, alternative and relatively novel data sources may become available which would provide similar information on visitor flows from accommodation sites or major attractions to individual stores. One such example would be via mobile phone data, with commercial products, such as Telefonica's 'Smart Steps' increasingly becoming available for use by retailers[43]. The academic community also recognises that telecommunications companies collect and hold a wealth of spatially referenced data that may provide new insights into consumer behaviours. Telefonica's 'Smart Steps' product, for example, makes use of data collected each time a mobile phone handset 'checks in' with the mobile network, with these 'network events' taking place frequently as a mobile phone picks up network coverage from different masts. The 'Smart Steps' product makes one use of this data to identify footfall around retail centres at different times of day or different days of the week, based simply on the presence of a mobile phone within pre-determined grid squares (with no details about the phone itself, or it's registered user available). Telefonica are keen to develop additional data sources for commercial application across the retail sector and similar data could potentially be utilised to obtain some form of flow data between large holiday parks and similar sites (and large grocery stores), assuming that the density of mobile phone masts within a destination of interest allowed handset locations to be pinpointed to a suitable level of accuracy. Such data, representing flows from large accommodation sites to stores, may be useful in understanding more about visitor's grocery consumption, especially identifying the importance of distance and the relative attractiveness of competing stores from a visitor's perspective, potentially enabling both alpha and beta to be calibrated specifically for visitor demand.

The third series of recommendations consider further the applicability of the modelling itself in a location planning context. The SIM is primarily for application in assessing the trading potential of supermarket, superstore or hypermarket developments. As noted in Chapter 2, whilst SIM has become an important tool for revenue prediction across the industry, it is not commonly applied for c-store (below 3,000 Sq Ft) development. Gell and Mulcahy (2013) and Brodley (2013) explain that the analysis of c-store trading potential places little reliance on the SIM, instead being concerned with footfall within an immediate catchment of up to around half a mile. Nevertheless, it is inevitable that a number of c-stores will be located within tourist resorts and similar destinations. Consequently, it is suggested that further work may seek to apply the small-area seasonal and spatial expenditure estimates for the assessment of c-store trading potential within the form of GIS buffer analysis commonly employed for this form of store-level analysis.

Furthermore, it is also recognised that the current modelling framework fails to account for online grocery shopping and instead assumes that all visitor expenditure is converted to in-

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[43] See: http://dynamicinsights.telefonica.com/488/smart-steps

store shopping. It is inevitable that a proportion of locals and visitors will shop online. Tesco and Waitrose have heavily advertised their online home delivery service as an alternative to store based shopping for visitors using self-catered accommodation (Tesco, 2010a; Waitrose, 2011). Whilst these services are often picked, packed and despatched from a local store, consumer choice over which retailer to use may be based far less on accessibility or store size and more heavily influenced by brand and the cost, reliability of availability of delivery slots. It is thus suggested that future work disaggregates both visitor and residential demand further within the model, identifying the proportion of expenditure thought to be via the online channel. Using retailers established knowledge of online shopping habits, separate model parameters could be applied to represent consumer decision making processes within the online grocery sector.

Fourthly, and turning attention to the expenditure estimates themselves, it is recommended that further work be undertaken to explore the availability of readily available or 'open data' sources, which could be used to identify as much of the accommodation stock as possible, for use in developing small area expenditure estimates. This thesis benefitted greatly from the support of two major tourist organisations operating at the local or regional level. It was acknowledged that retailers may lack such form of support, and the weaknesses in these databases (currency, completeness and consistency) were noted. In attempting to build seasonal demand layers for use as a site screening tool (rather than generating detailed revenue predictions), alternative data sources may provide a suitable indication of the overall provision of commercial accommodation.

For example, it was noted in Chapter 3 that the National Population Database (NPD) made use of the OS 'MasterMap – Address Layer 3' product to identify some forms of visitor accommodation, with some serviced accommodation, holiday parks and campsites listed. Whilst Smith and Fairburn (2008) noted a number of ommisions within this data, their main concern was the difficulty in 'populating' the available accommodation stock. Chapter 5 has demonstrated that it is entirely realistic to populate the accommodation stock based on surveyed occupancy and expenditure rates. It is therefore recommended that a full assessment of OS MasterMap, Open Street Map (OSM) or location-based listings within services such as Google Maps be explored fully to identify the extent of accommodation provision listed, and the feasibility of identifying details such as capacity and operating season so that occupancy and expenditure rates can be applied. The great benefit of these data sources is their national coverage, allowing demand layers to be produced and replicated consistently across large areas.

Finally, the small area seasonal visitor population estimates (prior to the addition of grocery expenditure rates) represent an advance in the understanding of spatial and temporal patterns of non-residential populations at a sub-district level (see Chapter 3 for a full discussion of the existing weaknesses here). Consequently, there are a number of additional sectors and applications for which these specific layers (or similar layers created for alternative years or

locations) could aid location-based decision making and service delivery. An understanding of accommodation provision and occupancy/utilisation rates, disaggregated at a small area level, allows a broader range of localised economic and social impacts to be identified. For example, and as noted in Chapter 3, attempts have previously been made to incorporate visitor populations within a National Population Database (NPD) for use by the UK Health and Safety Executive (HSE). Similarly, on-going work by Dave Martin and colleagues (e.g. see (Cockings *et al.* (2010); Martin *et al.* (2010); Smith *et al.* (2013)) seeks to generate small-area population surfaces which incorporate non-residential populations and identify temporal populations over seasonal, diurnal and more discrete temporal scales (as part of the *Pop24/7* project). The seasonal visitor population estimates produced within this thesis are of great interest to that project team, and on-going work between the author and the *Pop24/7* team seeks to embed the small area seasonal and spatial visitor population estimates for Cornwall (Chapter 5) within their surface population models, specifically for assessment of exposure to natural hazards, building on on-going work by Smith *et al.* (2013).

Alongside retail provision, the small-area seasonal and spatial visitor numbers could be used to aid alternative forms of service provision and delivery. As one example, knowledge of the location and likely numbers of overnight visitors (at a local level) assists greatly with the provision of health services. In Cornwall, for example, health services experience an influx of tourists requiring treatment in the summer, exerting pressure on NHS staff and reducing the availability of services for local residents (Cornwall Single Issue Panel, 2004). Being able to estimate small-area visitor numbers at different points within the tourist season allows services such as this to plan appropriate provision and in, some cases (especially where sustained tourist demand exists), maintain the viability of smaller health facilities such as minor injury units (Cornwall Single Issue Panel, 2004). Commonly, decisions about these forms of service delivery are being made with very little knowledge of visitor numbers and their associated seasonal fluctuations and, as such, the visitor demand estimates assist greatly in understanding seasonal variations in visitor demand (which may not always represent expenditure) across a whole range of service provision.

The further development and future research outlined within this section highlights that there are a number of enhancements that could be made to the SIM and the small-area demand estimates. These additions, some of which would require considerable work or data input, may further improve the accuracy of the demand estimates or the ability of the model to predict store-level revenue with accuracy. They would also extend the impact of this work beyond the grocery retail sector, addressing some of the weaknesses identified within the review of existing academic and industry literature. Whilst certain improvements and extensions could be made, these should not detract from the considerable progress that has been made within this thesis. Whilst obvious scope for improvement exists (particularly via provision of flow data enabling identification of 'observed' visitor demand flows), this thesis has succeeded in meeting its objectives, as noted in section 9.5.

9.5 Concluding remarks

Seasonal demand, in the form of demand generated by visitors (tourists), impacts upon both origins and destinations across a whole range of services. Charles-Edwards (2011), p53 notes that "[the] constant flux of population has diverse and far-reaching implications. It alters the demand for goods and services at both origins and destinations: for water and energy, for housing, for food and consumables, for roads and parking, for rubbish collection". In spite of its importance as a generator of demand fluctuations, little is known about the localised impact of visitor demand on many services. This thesis sought to address one form of visitor demand uplift, that of expenditure on groceries within destinations.

This thesis has addressed its overall aim(s), which sought to develop modelling techniques that can be used (within site location research) to estimate store revenue with accuracy in tourist areas. As outlined within this chapter, this thesis has developed a modelling approach (building visitor demand from the bottom up) and a specific model (calibrated for 2 large areas) that can be used to estimate grocery store revenue and seasonal sales fluctuations to a very acceptable level of accuracy. Birkin *et al.* (2010a), p442 note that "models must be seen to work in the most obvious sense – they must reproduce known trip patterns and store revenues". This thesis demonstrates that the modelling framework produced is able to do so, with further improvements identified that would allow calibration against a greater range of flow data.

Ince and Jackson (2012) assert that it is increasingly important for retailers to exploit the potential of academic research in order to best prepare themselves for continued challenges in this sector. They note that the recent appointment of 'Retail Knowledge Navigators' including Keith Dugmore (Demographic Decisions Ltd.) and Paul Longley (UCL) seek to develop strategies to help retailers make use of academic input and expertise to support decision making. Retailers could make extensive use of academic expertise in handling the vast quantities of spatially referenced consumer data they have available, and this CASE award highlights that productive and effective collaborations can be developed, addressing both academic and commercial objectives. From the perspective of an early career researcher, this collaboration has provided an exciting opportunity to work on an issue of both commercial and academic significance and to contribute to the on-going research agenda.

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Appendix: A note on Census Geographies

The bulk of the work contained within this thesis has been carried out prior to the release of 2011 small-area census data. Boundary changes mean that it is not straightforward to combine data from the 2001 and 2011 censuses, yet population increased considerably (by 6.6%) in Cornwall between the 2001 and 2011 censuses. It is thus important to incorporate up-to-date population or household estimates within small-area modelling. Many of the non-census products used (for example drive-time data, Sainsbury's market share and consumer flow data) remain compatible only with the 2001 census geographies. Consequently, modelling has been carried out using 2001 census geographies, but 2011 census counts of households and residential population have been applied. This appendix provides more detail on how data from the two censuses have been combined, taking account of boundary changes.

The 2001 OAs were constructed in 2003, built from clusters of unit postcodes as at census day and constrained to 2003 admin boundaries. They will be referred to here as '2001 OAs'. The 2001 OAs were designed to provide stable geographies and a consistent base for reporting small-area statistics over time. However, they were also constructed around the premise that they would have approximately equal household and population counts, relatively homogeneous social characteristics and fall within certain threshold populations (both maximum and minimum), in part to avoid the disclosure of confidential information about households or individuals.

As a result of the population changes identified within the 2011 Census, the OA boundaries were reviewed and some changes were made to ensure that the release of small-area data from the 2011 Census used OAs that were fit-for-purpose. Changes took place where:

- A significant change in population or number of households had taken place such that the population/households exceeded 625 or 250 respectively, or fell below 100 people or 40 households.

- Changes to local authority boundaries meant that OAs were no longer wholly contained with their parent local authority (based on local authority district boundaries at 31st December 2011).

- In exceptional cases, where an expert panel identified that an existing OA was otherwise unsuitable for statistical outputs, for example where there was no social homogeneity.

Following these changes, the average population per OA in Cornwall has increased from 284 to 297 people, and the average number of households has also increased from 122 to 129.

Whilst the changes may be minimal, all recorded changes (which include merging and splitting existing OAs along with boundary alterations) result in changes to the underlying census geography, with impacts on small-area expenditure estimation, such that the 2011 population and household counts must be incorporated in these estimates. Within Cornwall a total of 34 OAs underwent some form of change, with 22 of these representing larger OAs that were split, and 12 OAs fell below minimum threshold values and were merged with adjacent neighbours, shown in Table A.13.

Table A.13 - Changes to Census Geographies, Cornwall

Cornwall	2001	2011
Number of OAs	1,758	1,792
Number of OAs merged	12 OAs merged to form 6 new OAs	
Number of OAs split	22 OAs split to form a total of 62 OAs	
Total Population	499,114	532,300
Population per OA	284	297
Population per OA increase	4.6%	
Total Households	214,770	230,400
Households per OA	122	129
Households per OA increase	5.2%	

As a result of the changes to the census geographies highlighted in Table A.13, outputs from the 2011 census cannot be directly applied to any other small area statistics and vice-versa. Even where the physical characteristics of OAs have remained consistent between the 2001 and 2011 OAs, all OAs have been renumbered. These changes represent a considerable challenge for the modelling employed within Chapters 6 and 7, and subsequently within Kent in Chapter 8. The models used in Chapters 6 and 7 were developed prior to the release of 2011 Census data and geographies were available. The various data 'products' used were largely built on 2001 census geographies and underlying data including the OAC, second home counts, travel time data, retailer market shares and flow data. Three original research publications were also based entirely upon 2001 Census geographies, and these have not been changed in light of new data availability.

The models produced in this thesis are therefore built upon 2001 census geographies, but incorporate 2011 household counts. This has been achieved using an ONS lookup table[44] that allows 2011 OAs to be linked to their respective 2001 OAs. 12 Cornish OAs from the 2001 Census geographies have been merged and represent only 6 OAs in the 2011 data, whilst 22 OAs from the 2001 OAs are now represented by 62 OAs in the 2011 dataset. Consequently, for these OAs it is not possible to directly apply population and household counts from the 2011 Census by using the 2001 boundaries,

Dealing first with the 2011 OAs that result from the splitting of larger 'parent' OAs, Figure A.11 highlights the process used. The 2011 OAs with their respective population or household counts can simply be re-aggregated to their 'parent' 2001 OA, adopting the sum of household and populations recorded within the subsequent 2011 OAs. Considering the 12 OAs where merges have taken place, the 2011 population and household counts from the merged OA have been disaggregated across the original un-merged 2001 OAs, in relation to their 2001 household and population distribution, as illustrated in Figure A.12.

Whilst it is acknowledged that this is a crude approach, it is considered sufficient to generate small area household counts that make use of the most timely data source. 2011 household and population counts have been applied to 2001 census geographies for use in demand estimation and modelling at an OA level. The approach outlined here refers to residential demand estimates only. All other data, including all forms of visitor demand and interaction (road travel time) used within the modelling have been obtained or modelled directly within 2001 census geographies and have not required the processing outlined above.

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[44] Available via: http://www.ons.gov.uk/ons/guide-method/geography/products/census/lookup/2001-2011/index.html
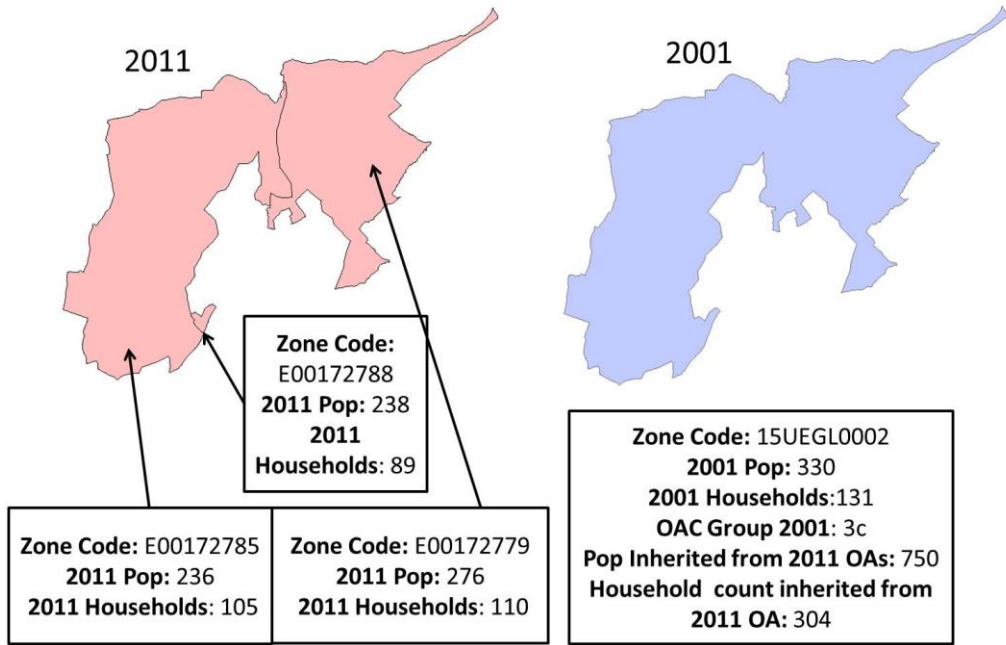
Figure A.11 - Application of 2011 OA household and population counts to 2001 pre-split OAs.
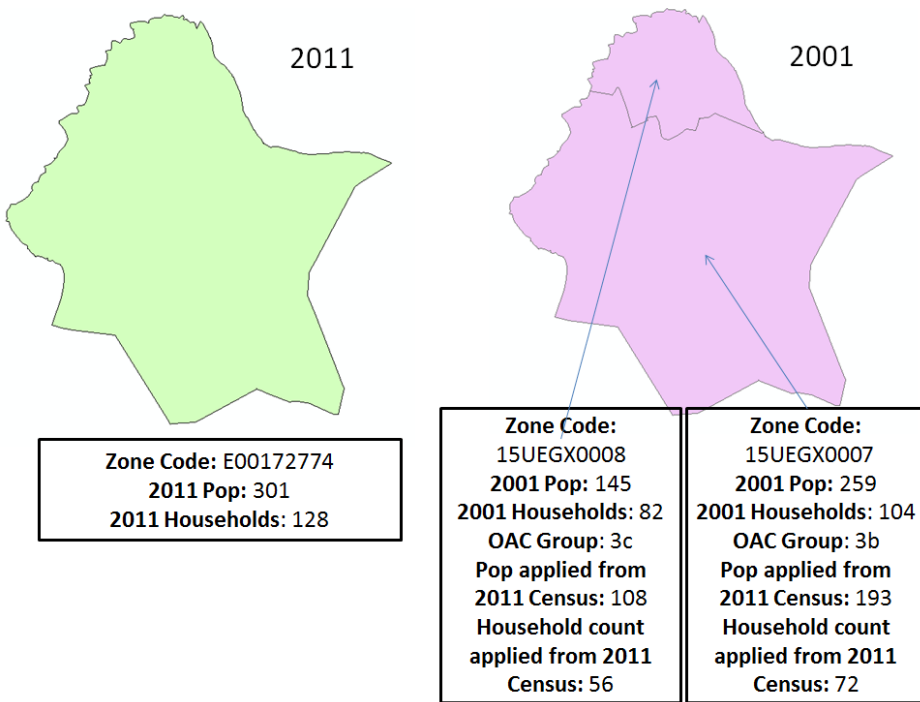

Figure A.12 - Application of 2011 OA household and population counts to 2001 pre-merged OAs