Abstract

Purpose

21st century online retailing has reshaped the retail landscape. Grocery shopping is emerging as the next fastest growing category in online retailing in the UK, having implications for the channels we use to purchase goods. Using Sainsbury's data, we create a bespoke set of grocery click&collect catchments. The resultant catchments allow an investigation of performance within the emerging channel of grocery click&collect.

Design/ methodology/ approach

The spatial interaction method of 'Huff gravity modeling' is applied in a semi-automated approach, used to calculate grocery click&collect catchments for 95 Sainsbury's stores in England. The catchments allow investigation of the spatial variation and particularly rural-urban differences. Store and catchment characteristics are extracted and explored using ordinary least squares regression applied to investigate 'demand per day' (a confidentiality transformed revenue value) as a function of competition, performance and geodemographic factors.

Findings

Our findings show that rural stores exhibit a larger catchment extent for grocery click&collect when compared with urban stores. Linear regression finds store characteristics as having the greatest impact on demand per day, adhering to wider retail competition literature. Conclusions display a need for further investigation (e.g. quantifying loyalty).

Originality/value

New insights are contributed at a national level for grocery click&collect, as well as e-commerce, multichannel shopping and retail geography. Areas for further investigation are identified, particularly quantitatively capturing brand loyalty. The research has commercial impact as the catchments are being applied by Sainsbury's to decide the next 100 stores and plan for the next five years of their grocery click&collect offering.

Keywords

Retail geography, click & collect, spatial interaction modelling, retail catchments, linear regression, retail patronage.

Introduction

Grocery shopping has emerged as a rapid growth sector within online retailing (Kirby-Hawkins et al., 2018; Mintel, 2016). Online grocery shopping increased 29% annually (2014 to 2016) and is predicted to grow further (Mintel, 2016). The observed escalation has incentivized major grocery retailers to implement innovations to more effectively meet increasing demand (e.g. channel and delivery options). In addition retailers have refined their offerings as well as providing product quality and freshness guarantees which have allowed click&collect to become the alternative to home delivery (Birkin et al., 2017).

As an increasingly important and sought-after innovation, click&collect is associated with a technology-savvy customer and a shift towards convenience, as customers demand a seamless shopping experience (Kirby-Hawkins et al., 2018; Wrigley and Dolega, 2011). Currently, all major UK grocers operate within the space of e-commerce, however few have offered long-term grocery click&collect services (e.g. Sainsbury's launched click&collect in 2014). Despite growth, the channel comes at an additional cost, is less predictable and is more onerous to operate (Mintel, 2016). Grocery e-commerce expands from the traditional grocery store (Yrjölä, 2001) requiring additional complex infrastructure that is only viable within high revenue stores. Sites selected for grocery click&collect require further infrastructure to accommodate specific online facilities (e.g. refrigerated storage and collection points), typically expanding into car parking facilities. As such, informed site selection plays a vital role in maximizing profits in the emerging channel.

Faced with infrastructure challenges, retailers must make strategic decisions regarding facility location and network rationalization (Birkin et al., 2017), whilst accounting for performance and competition. Recent advances in e-commerce and consumer expectations have encouraged a reassessment of analytical techniques applied to brick and mortar stores (Singleton et al., 2016). Click&collect facilities are multifaceted with the inclusion of both convenience as well as propensity for online shopping. Retailers must consider the relationship between online sales and existing networks of competing physical stores where traditional business performance metrics are becoming obsolete (Deloitte, 2017). This poses a significant challenge to analysts who are required to demonstrate both location analytics and data science skillsets. Indeed, site selection is increasingly becoming enhanced by data science with data available through automation, digitization and shopper profiling.

Whilst both traditional and online sales are widely studied areas in retail and consumer analytics, there is little quantitative research present (Ganesh et al., 2010; Kirby-Hawkins et al., 2018). There is a knowledge gap pertaining to grocery click&collect patronage and the factors likely to govern the channels performance. Of key significance is the extent to which traditional catchment estimation methods can be applied to click&collect services, and how conventional location-support factors used for brick and mortar grocery retailers intersect with the performance of these stores.

The aims of this paper are twofold. Firstly, we aim to explore the performance of grocery click&collect facilities geographically using real-world data supplied by a leading UK grocery retailer, Sainsbury's. Secondly, we aim to provide some understanding of grocery click&collect that can address the knowledge gap within e-commerce and multi-channel grocery shopping. Focusing on grocery click&collect in isolation brings new information to the wider study of patronage decisions and retail geography. More specifically, we analyze the spatial variation in performance of grocery click&collect and the extent to which competition and other factors affect demand. The study attempts to delineate potential catchments for grocery click&collect services considering store attractiveness, competition and distance between consumer domicile and collection facilities. We then explore statistical significance of store characteristics and catchment demographics that can be associated with performance within a grocery context. This paper has a strong commercial value due to rarity of similar studies specifically regarding the access to data. Our applied methodological approach can be implemented to a real-world scenario and as a result of this study Sainsbury's have implemented the resultant catchments in planning for the next five years of grocery click&collect operations and the location for their next 100 click&collect sites.

Literature review

The emergence of the Internet as a retail channel made it cost-efficient for store-based retailers to offer e-commerce services (Chatterjee, 2010; Hand et al., 2009). Stores with Click&collect facilities act as distribution centres for online channels, however in rare applications stock is fulfilled by larger nearby stores and transported to the collection point. The concept reduces the carbon footprint, reducing failed deliveries with theorized trip reduction as customers will walk or cycle for 'top up shops' (Pan et al., 2017; Roby, 2014). Although the process is innovative, there has been multichannel implementation issues seen in France (Colla and Lapoule, 2012). Increasing knowledge of the channel will help benefit future implementation.

Click&collect in grocery stores

Growing competition, stricter planning legislation and perceptions of increased market saturation motivate retailers to continually innovate (Birkin et al., 2017). Grocery click&collect is an emerging channel where analysis is predominantly performed by private sector research companies (e.g. Mintel). Existing literature consists of an online vs. physical purchase approach, often considering the whole shopping experience (e.g. Ganesh et al., 2010). Consumer profiling is a predominant theme (e.g. Harris et al., 2017) and as such there are opportunities for research that focuses on factors driving e-commerce (Doherty and Ellis-Chadwick, 2010).

Although new, 48% of shoppers have used grocery click&collect, with the estimated market share of 6% in 2015, doubling from 2010 (Mintel, 2016). The channels popularity is expected to increase further as online services offer tangible benefits to the necessity of grocery shopping (e.g. avoiding checkout queues or crowded stores) (Roberts et al., 2003; Harris et al., 2017). Similar drive-through collection facilities in France have witnessed high usage resultant of heavy investment intended to avoid home delivery and last mile costs (Colla and Lapoule, 2012; Lapoule, 2014). Considerable investment has also occurred in the UK (e.g. Sainsbury's opened 100 sites in a year), however the perishable nature of groceries and the resulting infrastructure requirements fundamentally inhibit potential. Click&collect is inherently a supplementary channel as physical stores are considered the staple and key element (Hand et al., 2009; Harris et al., 2017; Jones and Livingstone, 2015). The shopping process is fundamentally hybrid, regularly involving online research where additional product information is available.

Multichannel offerings can therefore be conjunctive and can benefit traditional store performance (Harris et al., 2017; Roby, 2014; Weltevreden, 2007). Efficiency is becoming a key component of strategy in order to maximize margins in the grocery retail environment (Lapoule, 2014). The UK grocery industry is considered one of the most efficient in the world, where logistics have become demand driven and grocers control the majority of marketing and supply chains (Fernie et al., 2010). To maintain efficiency retail stores have evolved to become multifaceted, acting as amongst other things distribution centres for the online operation. A successful e-commerce operation requires distribution network and last mile efficiency. This in-turn will allow for the control of cannibalization (Doherty and Ellis-Chadwick, 2010; Fernie et al., 2010).

Customers have two points of interaction (online and at the collection point). Significant e-commerce infrastructure of real time product and stock level information are required. Design can influence purchasing and patronage (Emrich and Verhoef, 2015; Yrjölä, 2001) and accurate information is vital to avoid 'out of stocks' and unnecessary additional costs (Lapoule, 2014). Site information is similarly important as purpose-built storage and collection facilities are required, which are typically located in parking areas. Importantly, click&collect must combine all these factors to offer buying environments that enhance customer purchase probability (Thanh et al., 2017), where cost is a fundamental limitation

(Doherty and Ellis-Chadwick, 2010) and perceptions of service quality and efficiency are considered influential (Lapoule, 2014; Thanh et al., 2017).

Retail store performance in the multi-channel era

Retail stores are traditionally classified based on location and size. Typically, large, high revenue stores in key locations (flagships) allow the feasibility of expensive facilities. For Sainsbury's grocery click&collect, Canopy (a rain canopy over a collection point) is the most expensive format and is reserved for such high revenue stores. Despite research recognizing different formats with pricing, promotion and multichannel exploration, research suggests that online is predominantly used for comparison whereas physical stores are used for purchase (Grewal et al., 2009; Roby, 2014). To target customers and generate multiple routes to purchase, retailers are increasingly adopting multichannel strategies (Agatz et al., 2006). However, one of the implications is that this increases complexity of performance measurement. Measures traditionally include profit, store traffic (Walters and MacKenzie, 1988) and return on sales (Lewis and Thomas, 1990). Recent measures range from checkout waiting times or the number online order items substituted.

Although online purchasing is considered complementary with traditional physical shopping never completely ceasing (Hand et al., 2009; Roby, 2014), penetration of online sales is constantly increasing. Additionally, it can be argued that patronage decisions are fitful in nature, where destination has been linked with affluence, showing a relevance for understanding e-commerce (Doherty and Ellis-Chadwick, 2010). Influences of channel usage include time, effort, risk, financial cost (McGoldrick, P., Andre, 1997; Palmer et al., 2000) and efficiency (Lapoule, 2014). Online channels have been argued a compromise, removing the need to go in-store, whilst adding the inconvenience of accepting deliveries (Harris et al., 2017). Additionally, socio-economic factors are linked to brand loyalty (McGoldrick, P., Andre, 1997). Recent research focusing on understanding consumer purchase channel selection (e.g. Harris et al., 2017) has provided new and valuable insights, however the search for innovation is accelerating. The multifaceted nature of customer attraction requires further investigation (Ortegón-Cortázar and Royo-Vela, 2017).

Besides store characteristics and socio-economic catchment profiling, competition plays an important role in store performance. Market leaders, despite having size advantage, witness demand cannibalization from multichannel offerings. Demand is ultimately finite in nature and literature indicates retail channels have the potential to be both complementary and competitive. Birkin et al. (2017) discuss weekly zone expenditure (the amount of spending that can come from an area) which inherently limits market saturation. Because characteristics are intertwined with weekly zone expenditure, site planning must consider these factors. Regardless of total demand being fundamentally finite, multi-channel offerings may instead influence competitive advantage perception. Shopping environments have been found to influence patronage with size commonly seen as key to attractiveness (Dolega et al., 2016; Huff, 1963; Ortegón-Cortázar and Royo-Vela, 2017; Sevtsuk and Kalvo, 2018). Our studies relevance comes from providing specific understanding of the grocery click&collect channel in isolation and could be key to resource optimization, and wider multichannel planning (Grewal et al., 2009).

Location analysis approaches

The availability of better information has been a substantial innovation for retail. Retailers know more about their customers and networks, which in-turn allows methodologies that can benefit both immediately and long-term (Birkin et al., 2017). Although formal locational analysis has been available for over 50 years, the rise of low cost computing has led to the adoption of statistical analysis in the

decision-making process (Hernández and Bennison, 2000). Societal infrastructure evolutions and urbanization has advanced the data landscape, becoming fine resolution and heterogeneous (Arribas-Bel, 2014). The ability to utilize big data is available with advanced computing at a reduced cost (Boyd and Crawford, 2012; Kitchin, 2014; Laney, 2001).

Spatial Interaction Models (SIM) grouped under 'gravity models', are commonly applied in location analysis, accounting for geography, travel and spatial interdependencies (Trienekens and Willems, 2007; Wilson, 1971). At the core of SIM's is the interaction between an origin and destination. Early applications of SIM's occurred in the 1960s (Guy, 1991; Huff, 1963), however advancement and wider commercial application came in the 1990s (Guy, 1991). More recently, application has occurred with patronage estimations for individual grocery stores (De Beule et al., 2014) or entire retail and shopping centres (Dolega et al., 2016; Ortegón-Cortázar and Royo-Vela, 2017; Sevtsuk and Kalvo, 2018). Various patronage likelihood thresholds can be used to delineate catchment area for a store and then analyse consumer demographics. Nevertheless, grocery click&collect has received little attention in that respect as often the traditional private sector applications consist of business intuition and linear catchments. Applying SIM's at a national level utilizes and allows for a consistent methodology to be applied in-parallel whilst accounting for internal competition.

Methods

Click&collect catchments

Online shopping is typically influenced by factors such as age, price and convenience (Joseph and Kuby, 2011; Singleton et al., 2016). Socio-economic characteristics have influence (McGoldrick and Andre, 1997). Our approach to delineate catchments involves applying gravity models based on Newtonian laws of physics (Joseph and Kuby, 2011). We use a bespoke Huff model; a type of gravity model for spatial interaction used to analyze market areas of retail outlets (Griffith, 1982). The modelling technique introduced by Huff (1963) played a pioneering role in delineating retail catchments. The insight that consumers shop based on attractiveness and not closest distance is enacted, focusing on origin data to explain patronage decisions (Joseph and Kuby, 2011).

Huff can establish 'the areal extent from which the main patrons of a store will typically be found' (Singleton et al., 2016). One strength is simultaneous probability estimation for multiple stores (Joseph and Kuby, 2011). The trade area is delineated as a probability surface representing customer patronage (Dramowicz, 2016). Other simpler methods (e.g. concentric rings or Thissen or Voronoi polygons) assume a monopoly and don't account for existing stores, thus Huff is considered advanced and superior to other methods (Dramowicz, 2016), although historically has been restricted by computational power. The probability P that a consumer located at i will shop at store j is calculated using the formula (Huff, 2003):

$$P_{ij} = \frac{A_j^{\alpha}\, D_{ij}^{-\beta}}{\sum_{j=1}^{n} A_j^{\alpha} D_{ij}^{-\beta}}$$

- A is the measure of attractiveness for store j,
- D is the distance from i to j,
- α is the attractiveness parameter estimate for empirical observations,

- β is the distance decay parameter estimate for empirical observations,
- n is total number of stores including j.

Our application considers competing Sainsbury's grocery click&collect sites, their attractiveness, and distance between customer domicile and the nearest store. Attractiveness (the expected cost and reward (Dennis et al., 2002)) is linked to the value equation and loyalty (McGoldrick and Andre, 1997), with supply side factors playing a crucial role in decision-making (Birkin et al., 2017). Attractiveness is typically size based, however using further variables allow for better explanation and better captures the multifaceted nature of attraction (Dolega et al., 2016; Ortegón-Cortázar and Royo-Vela, 2017). Standardized store characteristics including trade intensity (sale intensity per size of store), sales area, store format average sales, average weekly transactions and competitors within a 2km buffer were combined to create our index of attractiveness.

Catchments were generated using the shortest distance road networks method in the *huff-tools* R package (Pavlis et al., 2014). The non-linearity in the attractiveness of the nearest stores (walking distance of 0.5km) was accounted for by increasing the alpha exponent. Additionally, retailer transaction data was used to define a 15km distance constraint based on the upper quartile of distance travelled to nearest stores. Stores operating for less than 100 days were removed from analysis to account for promotion saturation upon initial store opening (Birkin et al., 2017).

Using the above specifications, Huff probabilities for each Lower Super Output Area (LSOA) in England were then computed. To delineate the spatial extent of catchment areas the probability threshold of 25% was applied. This accounted for external competition as customers typically use multiple providers. The delineated catchments were scrutinized utilising expertise from location analysts at Sainsbury's, combining industrial intuition with theory led catchment estimation.

Figure 1 shows a complex pattern to demand. The largest demand is found in southern stores particularly near London, however, values vary throughout the England with no distinct region of significantly greater performance. Density of stores using the click&collect facilities is higher in the south, where internal competition impacts catchment size. Overall, the catchments have a smaller extent in urban areas when compared to rural areas. Larger catchment areas nevertheless do not necessarily relate to more customers, which links to population density.

Regression models

To explore the statistical significance of factors that could explain the performance of click&collect facilities, linear ordinary least squares (OLS) regression was used. The rationale for using OLS was to explore demand as a function (and provide greater insight) of catchment characteristics that may influence performance.

Dependent variable

Demand per day - the dependent variable (shown in figure 1) - was generated using Sainsbury's Output area (OA) click&collect sales data, provided as confidentially transformed OA 'demand'. This refers to a monetary value of sales with confidentiality transformation with preservation of the relationship of figure (i.e. high values constitute greater sales). The values were derived from sales data multiplied by a constant and random error applied of -1 to 1%. More specifically, OA demand, provided with a nearest store name, was aggregated by store catchment and divided by the number of trading days for grocery click&collect. The originally available 113 stores were reduced to 95, removing trial and convenience stores, and stores open less than 100 days to exclude initial promotions (Birkin et al., 2017).

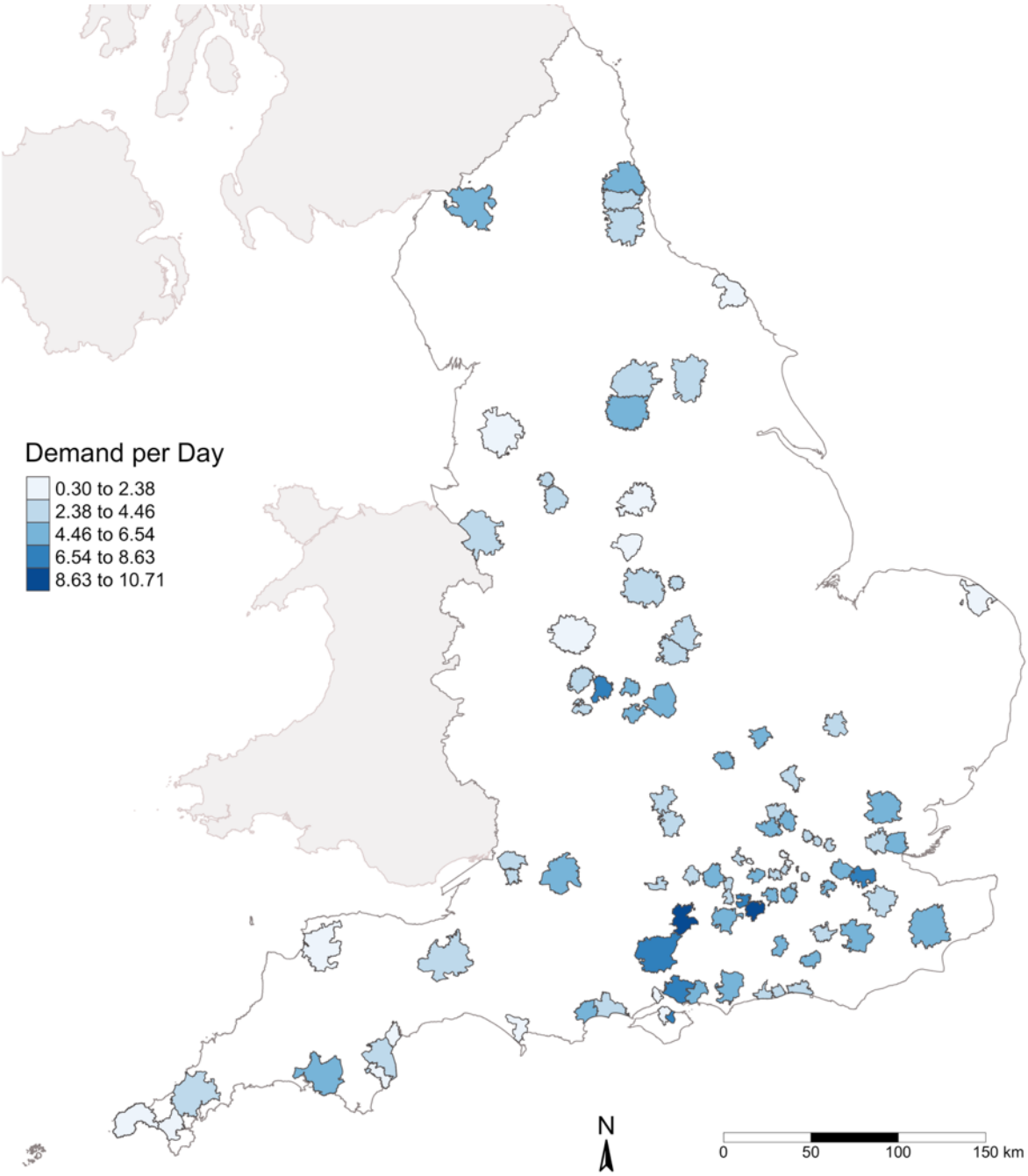

Figure 1. Site catchments and store demand (equal interval classification)

Competition measures

Predictors used to explain the variation in demand included competition, supply-related factors (store characteristics) and demand-related factors (catchment characteristics). Sainsbury's competition data contained competitors that offered a similar product range, sales area and format. Since Click&collect is reserved for higher revenue stores, stores smaller than 'supermarket size', less than 15000ft^2 (GeoLytix,

2016) and those not considered major competition relative to the hierarchy of competitive position (Dolega et al., 2016) were therefore removed. The remaining 2297 competitors were compared with *Retail Points* (GeoLytix, 2016) open license data containing grocery store information and size, to assess accuracy. Sainsbury's considered competitors had an undercount of 107 stores when compared with (GeoLytix, 2016), however per catchment differences were minimal. For example, the number of Marks & Spencer and Waitrose stores differed between the two datasets, although the overall count and spatial distribution showed little overall variance.

Store characteristics

Store information from Sainsburys's was included to account for site attractiveness and the influence of this on purchasing and performance (De Beule et al., 2014; Dolega et al., 2016; Ganesh et al., 2010; Harris et al., 2017; Huff, 2003). Table 1 lists variables included.

Table 1. Store characteristic variables

Variable	Description
Sales area	grocery sales area within a store
	equal count groups 1 smallest to 5 largest
Trade intensity	sales intensity (popularity) of a store per area
	equal count groups 1 smallest to 5 largest
Trading hours (weekly)	total weekly operating hours of a store
GOnline	Whether products are picked at a store different to the collection store
	collection stores are not targeted for performance of the service
Canopy	a rain canopy over the collection point
	the most expensive format that provides customers with the best collection experience, reserved for high revenue stores

Catchment characteristics

Socio-economic and geodemographic information (Bibby and Shepherd, 2004; DFT, 2016; ONS, 2011, 2016; Riddlesden and Singleton, 2014) were used as a to consider customer catchment characteristics and act as a proxy for loyalty (McGoldrick and Andre, 1997). Rationale also came from the finding that socio-economic information were observed as a driver of click&collect patronage for Intermaché, specifically customers in an above average socio-economic category (Lapoule, 2014). Table 2 lists variables included.

Table 2. Catchment characteristic variables

Variable	Description
All cars	vehicle accessibility measure indicates ability to travel to and use vehicle orientated click&collect census 2011 (ONS, 2011)
British and Irish population	ethnicity indicator census 2011 ONS, 2011)
Managerial	combined higher and lower managerial wealth and education indicator NS-Sec ONS, 2011)
e-Rural	measure for internet engagement and usage (Singleton *et al.,* 2016) Internet User Classification (IUC) (CDRC, 2016)
Urban LSOA count	indicator of urbanization Rural Urban Classification (RUC) (ONS, 2011)
Work-zone population density	measure for daytime population (ONS, 2011)
Train station count	measure for commuting environment NaPTAN (DFT, 2016)

Results

Overall, four models were produced (table 3). The dependent variable *demand per day* is consistent in all the models. The first model explains this as a function of competition measures; second, performance measures; third, geodemographic measures; fourth, all measures to explore how the effects change, exploring dominant variables. We consider the three sets of features initially in isolation, then combined in the final model to account for the multifaceted nature of retail attraction (Ortegón-Cortázar and Royo-Vela, 2017).

Table 3. Regression results

	Dependent variable: *Demand per day*			
	Model 1	**Model 2**	**Model 3**	**Model 4**
Competition	0.024			0.013
	(0.021)			(0.019)
Sales area		0.496**		0.484**
		(0.214)		(0.220)
Trade intensity		0.323**		0.295**
		(0.125)		(0.137)
Trading hours (weekly)		0.068***		0.066***
		(0.020)		(0.023)
GOnline		-0.890**		-0.940**
		(0.373)		(0.402)
Canopy		2.294***		2.270***
		(0.387		(0.416)
All cars			-0.398***	-0.039
			(0.124)	(0.061)
British and Irish population			0.053**	
			(0.023)	
Managers			0.186***	0.038
			(0.062)	(0.052)
Workzone population density			-0.0001	-0.0002
			(0.0003)	(0.0002)
Train station count			-0.001	-0.036
			(0.052)	(0.033)
e-Rural (IUC)			-0.496	-0.068
			(0.480)	(0.325)
Urban LSOA count			0.005*	
			(0.003)	
Constant	3.718***	-3.194***	13.854***	-1.396
	(0.272)	(1.001)	(3.900)	(2.948)
Observations	95	95	95	95
R^2	0.012	0.570	0.237	0.587
Adjusted R^2	0.002	0.546	0.176	0.532
Residual Std. Error	1.854 (df = 93)	1.250 (df = 89)	1.685 (df = 87)	1.270 (df = 83)
Note:			*p<0.1; **p<0.05; ***p<0.01	

Model 1 finds that demand per day increases as competition increases. The retail competition literature observes that retailers will consciously cluster in agglomerations for commercial benefit (Teller and Reutterer, 2008), and the sign of the coefficient in the model suggests support for that hypothesis. However, the estimate is not found significant, leaving the question somewhat inconclusive. Additionally, the low R-squared of 1% shows external competition alone does not explain much of the variation and further investigation is necessary.

Model 2 focuses on store characteristics and finds all the coefficients significant. The model explains 57% (R-squared value) of the variation, considerably more than model 1. Sales area is shown significant, where an increase in size is related to increased demand per day linking to retail literature where sales area (or store size) is cited as being a key determinant of attractiveness (Dolega et al., 2016; Dramowicz, 2016; Huff, 1963). Trade intensity, Trading hours (weekly) and Canopy were found to be all significant and positively influencing demand. A higher value for each of these features infer better performing stores and therefore the results are as expected. Conversely, GOnline (whether items must be picked from larger nearby stores due to small product ranges) shows a negative relationship, however these types of stores are not targeted for performance related to channel, and as such less emphasis is put on these services.

Model 3 examines only socio-economic variables. All cars variable, which is significant and negative in our model, indicates that the number of cars in an area does not necessarily relate to greater demand for grocery click&collect. Despite click&collect appearing car-centric, it is not a requirement for use of the service. Managers (higher and lower managerial from NS-Sec) are shown positive suggesting wealth and/or education linking to increased demand per day. Affluence has historically influenced participation in e-commerce, particularly in connection with new online services (Doherty and Ellis-Chadwick, 2010). Being more affluent could mean that customers are more willing to utilise convenience services instead of discount retailers, however there are further psychological features we cannot account for (e.g. convenience motivation and social interaction avoidance) (Doherty and Ellis-Chadwick, 2010). The count of urban LSOAs within a catchment displays a positive coefficient which complies with intuition-based site selection as stores have historically been located in urban areas where population density is greater. This model explains 24% of the variation (R-squared), indicating the selected features of catchment profiles are important, however offer limited explanation.

The final model combines all the features previously considered in isolation, however two variables were removed as they exhibited high values in variance inflation factor testing which suggests multicollinearity. Store characteristics are the only significant features. Adding further variables to model 2 has had a limited performance increase of R-squared (57% to 58.7%). Store information is found as having the greatest impact on demand per day, likely due to sites requiring the revenue to support additional facility costs. Our literature review suggests loyalty to have a patronage effect, however this is difficult to quantify. Without a quantifiable loyalty measure other than socio-economic features, this analysis conforms with the gravity retail literature that store characteristics are an important influencer of attractiveness and thus performance (Dolega et al., 2016; Huff, 1963; Ortegón-Cortázar and Royo-Vela, 2017).

Concluding remarks

The Internet has changed the UK retail landscape influencing store performance, its drivers and consumer experience from purchase decision to product delivery. Currently, most retailers have integrated Internet channels to their existing business models which is perceived to strengthen market

hold (Birkin et al., 2017). Sophistication of digital markets has brought rapid change and contemporary customers expect convenience, wide product ranges and value (Wrigley and Lambiri, 2015). This has potential to increase business operation costs in order to be competitive, typically at the expense of profit margins (Deloitte, 2017).

Understanding how customers make online purchase decisions coupled with factors responsible for patronage behavior in the digital era is increasingly important for success. Research shows that innovation and an efficient multi-channel experience is vital for success (Sopadjieva et al., 2017). Grocery click&collect is one recent innovation that gives retailers a competitive edge in multi-channel portfolios, however there is little evidence that helps understanding the key drivers of store/network performance in the omni-channel era and possible future growth trajectories.

This study uses real-world sales data to examine the performance of click&collect services for the second largest UK grocery retailer, Sainsbury's. New insights into a wider debate of the impact of e-commerce on traditional brick and mortar retailers are provided. Grocery click&collect patronage catchments have been delineated and have been used to explore the statistical significance of factors impacting store performance.

The implications of our findings are twofold. First, the examination of potential extent of store catchments in the era of e-commerce implies that although the traditional spatial interaction models are still applicable, they require adjustments to account for new challenges related to omni-commerce dynamics. Our catchment model considers competition, distance between stores and consumer domicile, and store characteristics. Validation comes via calibration against actual OA customer flow data. Although our model provides a reasonable catchment spatial extent estimation and was implemented by the retailer to identify potential revenue cannibalization issues, it could be argued that its static nature is not fit for purpose in the emerging digital era. As such, a new more dynamic approach to customer patronage better capturing the attributes of e-commerce facilities and mobility flows of omni-channel shoppers, may be essential.

Second, it appears that Sainsbury's click&collect sales are driven by store characteristics with sales area and opening hours being key attributes in our models. There was little statistical significance of demand-related variables, as the factors representing catchment demographics explained only 24% of the variation in click&collect sales. This was apparent despite taking precaution in relation to typically distorted early sales in newly opened stores saturated with promotions due to the intricate interaction between sales and targeted marketing (Birkin et al., 2017).

One potential explanation pertains to the issue that demographics derived for static catchments have limited application to modelling the performance of click&collect facilities. On the other hand, the results may suggest a limited application of a data driven approach for location planning of Sainsbury's current click&collect facilities. This resonates closely with the intuitive approach taken by many practitioners across industry. Although some catchment demographics such as proxies for affluence and ethnicity appear significant, there is no evidence that internet shopping propensity, key to online shopping, has been considered. Moreover, no statistical significance of a single demand related variable in combination with the effects of store characteristics implies location planning was driven by internal competition. Overlooking the influence of external factors at micro level such as competing stores and catchment demographics indicates that the analyzed click&collect facilities are not currently reaching their full potential. In the long term, this may lead competitive advantage and a network efficiency loss (Birkin et al., 2017). To better understand these complexities and future growth, further research analyzing up to date performance of the well-established and newly opened click&collect facilities

implementing more robust data on competitors and capturing the dynamics of sales through mobile channels, is essential.

Nevertheless, the results of this study are significant to stakeholders engaged in a debate on the future of UK retail including academics, retailers and location planners. The study, underpinned by real-world data, provides novel insights into grocery click&collect facility performance and contributes to a research topic that is new and under-researched, but appears to grow in significance due to the increasing role Internet sales play in the contemporary retail landscape.

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