The use of disaggregated demand information to improve forecasts and stock allocation during sales promotions: a simulation and optimisation study using supermarket loyalty card data

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Abstract: Our work highlights the importance of using disaggregated demand information at store level to improve sales forecasts and stock allocation during sales promotions. Monte Carlo simulation and optimisation modelling were used to estimate short-term promotional impacts. Supermarket loyalty card data was used from a major UK retailer to identify the benefits of using disaggregated demand data for improved forecasting and stock allocation. The results suggest that there is a high degree of heterogeneity in demand at individual store level due to number of factors including the weather, the characteristics of shoppers, the characteristics of products and store format, all of which conspire to generate significant variation in promotional uplifts. The paper is the first to use supermarket loyalty card data to generate store level promotional forecasts and quantify the benefits of disaggregating the allocation of promotional stock to the level of individual stores rather than regional distribution centres.

Keywords: sales promotions; demand forecasting; Monte Carlo simulation; stock allocation; optimisation; supermarket loyalty card data.

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1   Introduction

It has been estimated that in 2012–2013 over £14 billion of the £55 billion invested in price promotions in the fast moving consumer goods (FMCG) sector could have been retrieved by better coordination of supply and demand (IPM, 2015). There is also evidence that price promotions are often implemented with limited understanding of the factors influencing demand and/or supply (O'Dwyer et al., 2009), resulting in missed opportunities for sales and the generation of avoidable promotional waste (IPM, 2015; Mena and Whitehead, 2008). This is particularly dangerous for businesses operating with tight margins and limited resources (Mirkovski et al., 2016; O'Cass and Sok, 2013; Felgate et al., 2012; Thakkar et al., 2008).

The promotional literature is inadequate in its treatment of this phenomenon, relying on highly aggregated scanner data and assumptions about the promotional planning process that do not reflect industry practice. This paper seeks to contribute to this area by illustrating the potential for improved demand and supply synchronisation in retail supply chains, through the explicit use of disaggregated demand information (supermarket

loyalty card data) for forecasting promotional uplifts and the allocation of promotional stock at the level of individual stores. The first section summarises the operations and supply chain management literature in relation to the promotion of FMCG in retail supply chains and identifies gaps in the existing body of knowledge in the second section. The third section discusses the research methodology and the results of the simulation and optimisation are presented in the fourth section. The paper concludes with recommendations for business practice and further research in the last sections.

2 Review of the promotions literature

The promotions literature can be divided into two distinct areas. One is concerned with the demand-side and is focused primarily on brand marketing strategy and consumer reactions to different promotional stimuli. The other is concerned with the supply-side factors and is focused primarily on the replenishment cycle and how the supply chain responds to promotional activity. Whilst we recognise the inter-disciplinary nature of research into retail promotions – the management and impacts thereof – and adopt a research methodology that accommodates both demand-side and supply-side factors, given the focus of this paper is on the improvement of promotions management through the more effective use disaggregated demand data we focus here on the operations and supply chain management literature.

2.1 Operations and supply chain perspective on the management retail promotions

An accurate estimate of consumer demand plays a key role in planning the logistical support for sales promotions, especially for production scheduling, inventory control, and delivery planning (Mantrala et al., 2009; Gligor and Holcomb, 2012). Sudden changes in customer demand during promotions act as a shock which creates stress in the supply chain. Linking demand data with upstream processes can help reduce the impact of variable demand (Taylor and Fearne, 2009). This integration of demand management with supply chain management is potentially important, particularly during the stock allocation and shelf replenishment stages of the promotional cycle (Gligor, 2014).

Distribution, replenishment, and operational integration during promotions can be achieved by linking inventory control with consumer demand (Gebennini et al., 2009; Gligor, 2014). This also helps in optimising resource allocation, which is particularly important for SMEs. However, this integration requires information visibility at the store level which is a challenge, particularly for SMEs due to limited technological capabilities (Mirkovski et al., 2016; Thakkar et al., 2008). Due to the limitation of space and the increasing number of products on promotion, the stock allocation is becoming a challenge for retailers, which is made all the more complicated by the heterogeneity of consumer demand and product attributes (e.g., perishability) (Gligor and Holcomb, 2012).

Promoted products are twice as likely to be out of stock as non-promoted products and shelf replenishment at the store level and distribution centre has been identified as one of the two biggest reasons for stock-outs during promotions (Gruen et al., 2002; Felgate et al., 2012). This can be greatly reduced by better coordination through

information sharing. If suppliers have better consumer information, they could help retailers in replenishment efforts, especially for distribution and store level management (Kembro and Selviaridis, 2015). Coordinated work of this kind is strongly dependent on the alignment of objectives of buyers and suppliers and the accuracy of demand forecasts. Detailed information about consumer demand at the store level has the potential to reduce stock-outs, as it gives both suppliers and retailers the visibility for making accurate and timely decisions about shelf space and stock allocation. A lack of collaboration in the supply chain results in less information sharing and an increase in inventory levels at every stage of the supply chain (Cho and Lee, 2015).

2.2 *The role of information sharing in the synchronisation of demand and supply*

Up-to-date and relevant marketing information is needed at every stage of the supply chain. The most important information for demand and supply synchronisation is the demand forecast (Kembro and Selviaridis, 2015). Improving forecast accuracy has been a key focus for collaborative efforts between retailers and suppliers in recent years. However, the focus has been too highly aggregated, at the level of the central warehouse or distribution centre (Pramatari and Miliotis, 2008), which takes inadequate account of the heterogeneity of demand and responsiveness to promotional activity at the store level (Pérez Mesa and Galdeano-Gómez, 2015).

As the heterogeneity of consumer demand increases so too should the amount of information required to forecast it (Kalchschmidt et al., 2006). Aggregating demand and applying a single model to forecast promotional sales for all stores leads to information loss and increased forecast error, which in turn affects inventory levels and reduces efficiency (Kembro and Selviaridis, 2015). This detailed analysis of both demand patterns and supply chain becomes even more important in a promotional environment, where clusters of consumers are affected by different environmental factors like weather, location, and store layout (Ailawadi et al., 2009).

Retailers are making increasing use of disaggregated sales data to segment their shoppers and design more targeted promotional events (Demoulin and Zidda, 2009). However, the use of this data for more accurate demand forecasting or process improvement upstream is limited (Evanschitzky et al., 2012; Kalchschmidt et al., 2006).

2.3 *Gaps in the literature*

The analysis of the interplay between demand and supply has received little attention in the promotion literature to date. The literature highlights the importance of the relationship between demand and supply side factors and the use of information in the context of promotional planning and execution. However, where such studies have been undertaken, it is invariably assumed that formalised processes for promotional management are fit for purpose and universally adhered to. Anecdotal evidence suggests this is rarely, if ever, the case, for a variety of reasons, including the aggregation of stock allocation decision to the level of regional distribution centres rather than individual stores and the lack of information sharing between suppliers, the majority of whom are reliant on electronic point of sales (EPOS) data which provides an accurate measure of what is sold but no indication of why or to whom. The availability of supermarket loyalty card data has the potential to fill this gap and provide more detailed demand intelligence

to inform promotional planning and execution. There are currently no published studies that explore this phenomenon.

The majority of empirical studies conducted thus far have used either:

a   scanner data, which is highly aggregated and therefore fails to capture the heterogeneity of demand within and between product categories and amongst different shopper segments

b   survey data which relies on claimed/reported behaviour and is therefore highly unreliable.

Thus, the second gap in the literature relates to the impact that the use of disaggregated sales data might have on the efficiency (reduced cost/waste) and effectiveness (sales uplifts) of price promotions.

Despite these gaps, the literature does highlight the important role that information plays in the decision-making process and the adverse consequences of inadequate consumer insight and inadequate sharing of information along the supply chain. However, there is little evidence that disaggregated sales data is widely or routinely used by supermarkets or their suppliers. Moreover, the bulk of the published research regarding the impact of price promotions is either focused on modelling consumer responses, using claimed behaviour or highly aggregated scanner data, or on stock allocation and replenishment processes that bear little resemblance to the way in which the majority of retail supply chains operate. Thus, in seeking to capture both demand and supply side factors in greater detail, this research focuses specifically on the use of disaggregated sales data, broken down by store format and shopper segment, in order to generate accurate demand forecasts, optimise stock allocation at the individual store level and, as a result, improve promotional performance.

3   Research methodology

3.1   Semi-structured interviews

The design of the simulation and optimisation models was informed by a number of semi-structured interviews with suppliers. Two product sectors were chosen with contrasting product characteristics:

1   branded, ambient products

2   own-label, fresh products.

Rapeseed oil was selected as representative of the ambient product category and two suppliers (marketing and/or account managers) were interviewed. In addition, the marketing and/or account managers of three fresh produce companies supplying apples, mushrooms, and carrots were also interviewed. A group of retail buyers was also interviewed to gain the retailer's perspective on the promotional process. The relevant personnel was interviewed either face-to-face or by telephone. An interview guide was developed based on key issues identified from the literature review and focussed on the different stages of the promotional planning and execution cycle and the use of demand information and the allocation of promotional stock.

3.2   Simulation model

The simulation of promotional demand incorporated three levels of disaggregation:

1   shopper profile

2   store format

3   level of customer penetration.

Shoppers can be broadly categorised as price sensitive or up-market, with price sensitivity shoppers being more likely to respond to promotions than up-market shoppers. This classification is supported by Kucera (2014), who has shown that shopper behaviour during promotions is strongly impacted by socio-economic factors.

Three different store formats of increasing size were considered: metro, supermarket, and extra stores. Stock levels and replenishment cycles vary considerably depending on the size of the store and previous research (Andrews et al., 2011) has identified that the accuracy of consumer demand models is improved when consumers are segmented into (homogenous) groups based on store format.

The third level of differentiation is the overall level of product demand, as measured by customer penetration. Stores in which baseline demand for a product is higher are likely to experience higher sales uplifts in response to any promotion relative to stores in which baseline demand is lower. This, in turn, can affect decisions relating to stock allocation at the start of the promotion and the rate of replenishment thereafter.

Figure 1   Conceptual model of product sales based on disaggregated demand
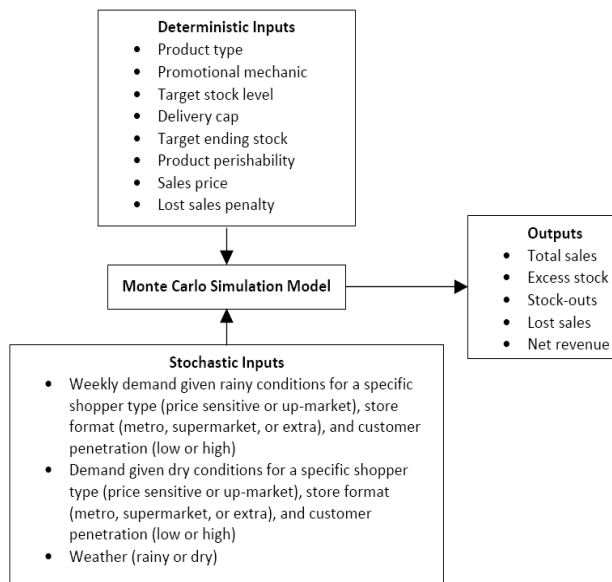
It is assumed that differences among shopper profiles, store formats, and levels of customer penetration will be exhibited by variability in demand for any given product type and promotional mechanism. These factors, in turn, should be helpful in making decisions relating to stock allocation and replenishment.

In an attempt to model the interactive effects of demand and stock allocation on expected net revenues, a suite of Monte Carlo simulation models was developed. A conceptual model of our simulation analysis is shown in Figure 1.

There are two main types of input to the simulation model: deterministic and stochastic. Deterministic inputs include the type of product, the type of promotion, stock delivery amount, sales price, a penalty for lost sales (due to stock-outs), the perishability of stock, and the target ending stock for a product (i.e., the desired stock level at the end of the promotion). The main stochastic factors are product demand and weather. Weather is independent, whereas demand is a function of customer profile, store format, customer penetration, and weather.

Four different product types were considered, including fresh (carrots and mangos) and ambient (rapeseed and sunflower oil). For each product, up to 12 different store classes were considered (three shopper profiles × three store formats × two levels of customer penetration). Each store class describes a specific combination of shopper profile, store format, and level of customer penetration. For each store class, a unique set of demand distributions was derived based on historical sales and weather data (see below for more details).

Figure 2 Stock control dynamics of the Monte Carlo simulation model
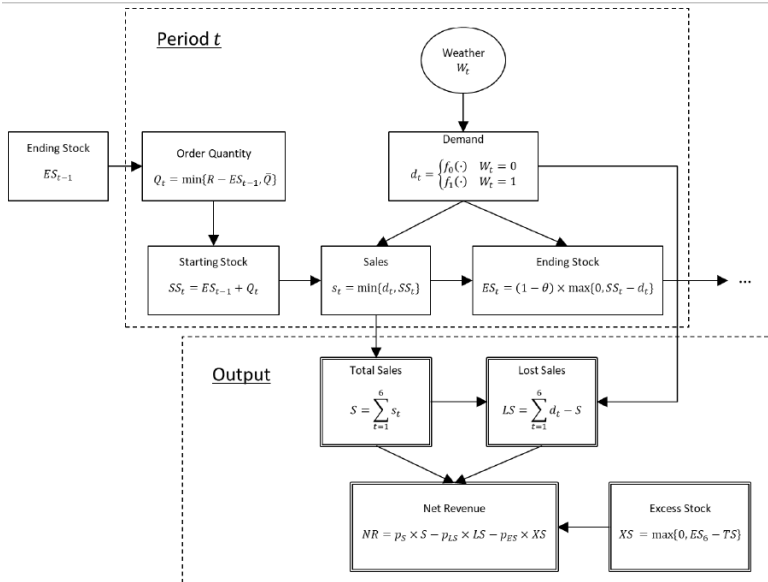
In the implementation stage of the simulation modelling process, a simplified stock-control model (Figure 2) was devised as follows. A six-week promotion cycle was adopted for all products. First, the weather condition W_t for a given week t was randomly generated according to a Bernoulli distribution, with $W_t = 0$ for predominately dry and $W_t = 1$ for predominately rainy conditions. The probability p of predominately rainy conditions was determined based on the average of majority rainy days per week prevalent during the promotion cycle (see Figure 2 for more detail).

For any given weather condition, product demand d_t for each week t was then randomly generated according to the distribution $f_{W_t}(r, m, n)$, where r is the customer profile (price sensitive or up-market), m is the store format (metro, supermarket, or extra), and n is the level of customer penetration (low or high). Note, there are, in fact two demand, distributions, one for dry conditions ($f_0(r, m, n)$) and one for rainy ($f_1(r, m, n)$). Sales s_t in week t was simply calculated as the minimum of demand d_t and the starting stock SS_t in week t (i.e., $s_t = \min\{d_t, SS_t\}$). This assumes that no short selling is allowed.

Inventory control follows a modified fixed-time period or periodic review ordering policy (Tayur et al., 1999). Here, orders are placed on a weekly basis, starting with the first week of the promotion cycle, in order to try to replenish stock to a set target level R. The amount of stock that can be order in any week, however, is capped to a maximum order size $\overline{Q}$. The delivery cap takes into consideration the fact that the total amount of stock at the distribution centre is limited and a store may not be able to order an amount sufficient to bring the stock back up to the target level (see optimisation model below). More specifically, inventory is checked at the beginning of the week and a variable quantity Q_t is ordered based on the following equation:

$$Q_t = \min\{R - ES_{t-1}, \overline{Q}\}$$

Starting stock is simply taken as the ending stock ES_{t-1} from the previous period plus the delivery amount (i.e., $SS_t = ES_{t-1} + Q_t$). The initial ending stock (i.e., just prior to the start of the promotion cycle) is equal to a value ES_0. Ending stock for any week during the promotion cycle, meanwhile, is estimated as the starting stock minus the amount sold times the carry-over fraction (i.e., one minus the fraction of goods θ lost due to perishability). More specifically, ES_{t-1} is determined by the equation:

$$ES_t = (1 - \theta) \times \max\{SS_t - d_t, 0\}$$

Finally, total net revenue NR was determined by the equation:

$$NR = p_S \times S - p_{LS} \times LS - p_{ES} \times XS$$

In the above equation, S is total sales $\left(S = \sum_{t=1}^{6} s_t\right)$ during the promotion, LS is the total lost sales $\left(LS = \sum_{t=1}^{6} d_t - S\right)$ during the promotion, and XS is excess stock at the end of the promotion period compared to the target ending stock TES ($XS = \max\{0, ES_6 - TES\}$). The parameters p_S, p_{LS}, and p_{XS} are the sales price, lost sales penalty, and excess stock penalty (all in monetary values). A penalty on lost sales was included in an attempt

to internalise losses due to stock-outs, while a penalty on having excess stock at the end of the promotion cycle was incorporated to prevent retailers from maintaining excessively high levels stock in an attempt to avoid stock-outs. Not only is keeping high levels of stock unrealistic (i.e., due to limited warehousing space) but it is also extremely costly both in terms of holding costs and wastage.

Besides a fixed-time period policy, we also considered a non-typical policy in which order quantities are constant each week. The reason for this is that for our particular case-study, the warehouse operator normally makes a fixed delivery amount a to all stores of a particular class. Under this policy, which we refer to as a 'fixed delivery' policy, the starting stock in any week was simply equal to the ending stock ES_{t-1} from the previous period plus the delivery amount (i.e., $SS_t = ES_{t-1} + a$). As part of our analysis, we compare the fixed-delivery policy against the fixed-time period policy.

Monte Carlo simulation models were implemented using the @Risk version 6.2 add-in tool for Excel. Simulations were run 1,000 times to compute expected net revenues $\overline{NR}$ and associated standard deviations for a given target inventory level R and delivery cap $\overline{Q}$ combination. The target stock level and delivery cap were then systematically varied up/down in set intervals to see how expected net revenue varied with target level and deliver cap. The same basic process was repeated for the fixed delivery policy by varying the delivery amount a up/down as well.

3.3 Data collection and analysis

Supermarket loyalty card data was used for the estimation of demand, before and during promotional periods. Weekly sales were analysed according to the three levels of disaggregation: shopper profile, store format, and level of customer penetration. Customer penetration (low or high) was based on the percentage of shoppers buying a particular product at least once in the previous 52 weeks. The following thresholds were used to distinguish 'high' customer penetration stores: $\geq 25\%$ for carrots, $\geq 7\%$ for mangos, $\geq 4\%$ for olive oil, and $\geq 5\%$ for sunflower oil. Promotional details were extracted from the same database and included product category, promotional mechanic and promotion dates.

During the semi-structured interviews, weather was universally identified as a critical (exogenous) factor that impacts on consumer demand. Thus, for the simulation of promotional demand, weather data, specifically daily dry/rainy conditions for each store locale, were obtained from the UK's Met Office. Over the duration of product promotion, each week was classified as 'rainy' or 'dry' if a majority of days met such conditions. The overall fraction of rainy weeks was then computed by averaging across all stores to come up with an aggregate likelihood of rain (p) during the promotion cycle.

3.4 Optimisation model

In order to efficiently allocate limited stock between a supplier and retail stores during a promotion cycle, a mixed integer linear programming (MILP) model was developed and implemented with the CPLEX 12.5 add-in for Excel. The model, which takes the form of the well-known 'multiple-choice knapsack problem',

is parameterised using the net revenue outputs from the simulation model. More formally let:

n the number of store classes, indexed by j

m_j the number of stock delivery levels, indexed by i, at store class j

d_{ij} the stock delivery amount associated with level i and store class j

v_{ij} the expected net revenue obtained from delivering stock level i to store class j

s_j the number of stores of class j in the distribution network

b the total amount of weekly stock in the distribution centre.

Note that parameter v_{ij} is equivalent to the expected net revenue $\overline{NR}$ output produced by the simulation model as a result of having a delivery cap/fixed-delivery amount i (parameters $\overline{Q}$ and a in the simulation model) at store class j.

We further introduce the following binary decision variables.

$$x_{ij} = \begin{cases} 1 & \text{if stock level } i \text{ is delivered to store type } j \\ 0 & \text{otherwise} \end{cases}$$

The problem optimally locating limited stock can then be formulated mathematically as follows:

$$\max \sum_{j=1}^{n} \sum_{i=1}^{m_j} s_j v_{ij} x_{ij} \tag{1}$$

s.t.

$$\sum_{i=1}^{m_j} x_{ij} = 1 \quad \text{for all } j = 1, \ldots, n \tag{2}$$

$$\sum_{j=1}^{n} \sum_{i=1}^{m_j} s_j d_{ij} x_{ij} \leq b \tag{3}$$

$$x_{ij} \in \{0, 1\} \quad \text{for all } j = 1, \ldots, n, i = 1, \ldots, m_j \tag{4}$$

The objective of the optimisation model (1) is to maximise total net revenue from all store classes j in the distribution network. Constraint (2) ensure that only a single stock level i is delivered to each store class j. Inequality (3) requires that total stock deliveries are less than or equal to the amount of total stock level on hand b in the distribution network. Finally, constraint (4) requires the stock delivery decision variables to take on binary variables.

For the purposes of this research, there were a total of four different parameterisations for the optimisation model, one for each product type (carrots, mangos, rapeseed, and sunflower oil). To generate parameter values v_{ij}, the simulation model for a given store class and product class were run across a range of delivery amounts i.

4   Results

In this section, we summarise the key findings from the semi-structured interviews before presenting the results from the simulation and optimisation modelling, in which we identify:

a   the significance of demand heterogeneity, at the different levels of disaggregation

b   the potential for improved promotional performance, by comparing the actual (historical) sales with the outcomes from the simulation and optimisation.

The interviews revealed that the retailer and their suppliers generally forecast promotional demand and plan promotional stock levels according to previous sales volumes, using total percentage sales volume uplifts as the key performance metrics. This is in contrast to the level of dis-aggregation reported in the literature (Ramanathan and Muyldermans, 2011; Thomassey and Fiordaliso, 2006). This aggregation masks the significant variation that exists in the response of different shopper segments and for different types of store. In addition, there was little evidence of collaboration with regards to the forecasting of promotional demand, a potential source of error and process improvement that has been previously identified in the literature (Garretson et al., 2002). Forecast error was universally acknowledged as a problem and, whilst variable, was reported as often being far greater than the 10%–30% reported in the literature (Nagashima et al., 2015; Mena and Whitehead, 2008). The Interviews also supported our supposition that disaggregated demand data was not used at any stage of the promotional cycle.

Figure 3   Distribution of net revenues from the sale of 1 kg carrots at up-market + extra stores (customer penetration level not included) given delivery of 2,100 units (see online version for colours)
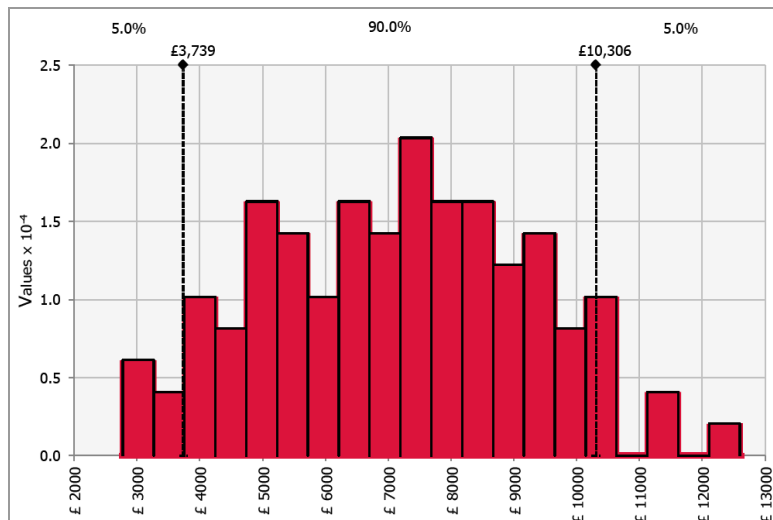
Table 1   Demand distributions for carrots

Customer profile	Price sensitive						Up-market					
Store format	Metro		Supermarket		Extra		Metro		Supermarket		Extra	
Customer penetration	*Low*	*High*	*Low*	*High*	*Low*	*High*	*Low*	*High*	*Low*	*High*	*Low*	*High*
Weather — Dry	Exponential β = 26	Uniform min = 50 max = 290	Gamma α = 3 β = 85.7	Exponential β = 320	Uniform min = 121.1 max = 768.8	Normal μ = 867.1 σ = 326.7	Uniform min = 0 max = 60	Exponential β = 70	Normal μ = 342 σ = 90.9	Triangular min = 480 max = 1,523.2 mode = 480	Uniform min = 610 max = 1,090	Triangular min = 452.5 max = 1,410 mode = 1,410
Weather — Rainy	Uniform min = 17.5 max = 82.5	Normal μ = 171.4 σ = 70.3	Triangular min = 10 max = 590 mode = 130	Triangular min = 300 max = 1,368.7 mode = 300	Weibull α = 1.3 β = 493.3	Uniform min = 387.3 max = 1,922.6	Triangular min = 16.6 max = 129.79 mode = 30	Triangular min = 90 max = 610 mode = 110	Normal μ = 487.8 σ = 233.4	Gamma α = 2.9 β = 183	Triangular min = 570 max = 2,069 mode = 570	Normal μ = 1,349 σ = 417.6

Table 2   Realisation of a single six-week promotion cycle for 1kg carrots sold at a price sensitive + supermarket + high penetration store

Inputs

Product/store/customer data		Demand specification		Stock control data	
Product:	1 kg carrots				
Store type:	Price sensitive	Prob. of rain:	0.7	Target stock (R):	600 units per week
Store format:	Supermarket	Demand | dry:	$f_0 = \text{Expo}(320) + 246.67$	Max delivery ($\bar{Q}$):	500 units per week
Customer penetration:	High (16%–22%)	Demand | rain:	$f_1 = \text{Triag}(300, 1{,}368.7, 300) + 246.67$	Init. ending stock (ES_0):	100 units
Perishability (θ):	0.7			Target ending stock (TES):	250 units
				Sales price (v_S):	£1.00 per unit
				Lost sales penalty (v_{LS}):	£1.00 per unit
				Excess stock cost (v_{XS}):	£1.00 per unit

Calculations

				Week				
	0	1	2	3	4	5	6	*Total*
Weather (w_t):		0	1	1	0	1	1	
Demand (d_t):		432	693	593	304	404	972	3,398
Sales (s_t):		432	550	500	304	404	547	2,737
Order (Q):		500	500	500	500	500	500	3,000
Starting stock (SS_t):		600	550	500	500	559	547	
Ending stock (ES_t):	100	50	0	0	59	47	0	
Stock-out (Y/N):		N	Y	Y	N	N	Y	

Outputs

Stock-out (Y/N):	Y
Total sales (S):	2,737
Lost sales (LS):	661
Excess stock (XS):	0
Net revenue (NR):	2,076

Table 3   Wilcoxon signed ranked test statistics (positive ranks) for different levels of demand disaggregation

| Product		Customer type			Store format			Customer penetration			Weather		
		Up-market vs. price sensitive						High vs. low			Dry vs. rainy		
		Extra	Super	Metro	Extra vs. supermarket	Supermarket vs. metro	Metro vs. extra	Extra	Super	Metro	Extra	Super	Metro
Fresh	Carrot	-4.112**	-2.756*	-1.863	-6.996**	-4.711***	-4.762**	-4.206**	-3.894**	-4.373**	-1.886**	-3.715**	-3.479**
	Mango	-6.473***	-4.001**	-3.759**	-4.223**	-6.513***	-7.753**				-0.949	0.343	-0.789
Ambient	Sunflower oil	-4.298	-2.500**	-2.500	-3.259**	-3.620**	-4.366**				-2.352	-3.402**	-5.084**
	Olive oil	-1.949	-1.143		-1.949						-1.634	-0.389	

Notes: *Significant at 5% level.
    **Significant at 1% level.

For the purpose of illustration, Table 1 shows the set of distributions and associated parameterisations used for carrots in the simulation model and Table 2 shows the simulation calculations/outputs for a randomly generated six-week period for 1 kg carrots sold at price-sensitive, metro, low penetration stores. Figure 3, which show an example of the summary output produced by the simulation model, namely the distribution of net profits (for up-market + extra stores).

Table 3 presents the results of the optimisation model, involving a comparison of historical and promotional sales broken into different levels of disaggregation. There are some interesting patterns observed in the levels of significance for different products and levels of disaggregation.

In the majority of cases, store format, customer type and penetration are important determinants of demand irrespective of a product category with certain exceptions like carrots in smaller store format (metro). Similarly, customer type is generally significant for fresh but not in ambient products (olive oil and sunflower oil). Store format is significant regardless of product class, the exception being olive oil. Weather is important for some products (carrots and sunflower oil) but not for others (mango and olive oil).

Figure 4   Comparison of total net revenue of optimised stock allocations (solid bars) versus stock allocations based on historical demand (hashed bars), (a) carrots (b) mangos (c) sunflower oil (d) olive oil

(a)   (b)

(c)   (d)
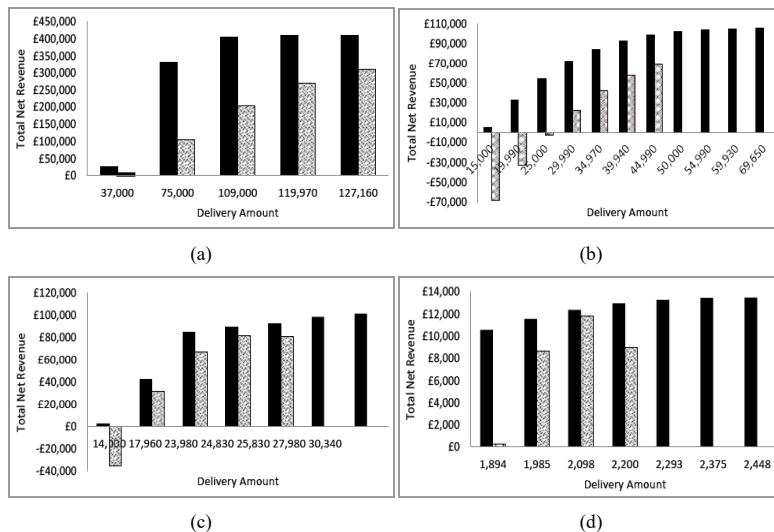
After validating all inputs to the simulation model four different line graphs were plotted based on the outputs of the simulation model which were fed into the optimisation model to derive the optimal net revenues. These optimal revenues were compared with the net revenues resulting from the current approach to stock allocation based on historical demand and are presented in Figure 4. Comparison of all the four products shows that executing sales promotions by taking into account the disaggregated level of demand by

customer type and store type results in higher percentage uplifts in the volume of promotional sales than those achieved using aggregated historical demand and stock allocation based simply on store size (e.g., extra stores receiving × times the promotional stock allocated to metro stores).

There are some interesting patterns within product categories. In the case of the fresh produce category (carrot and mango) as the delivery, amount increases the difference between the historical net revenue and optimal revenue decreases to varying degrees. This result is not observed in the ambient category. For example, the difference between historical and optimal revenue as delivery amounts increase first decreases and then increases at higher delivery amounts. Similarly, for initial increases in total stock, net revenue rises quickly but then taper off as stock levels catch up with demand. In the case of carrots, total net revenue increase from less than £50,000 to more than £300,000 when the delivery amount changes from 37,000 units to 75,000 units but it tapers off to £400,000 when the delivery amount increases from 109,000 units to 127,160 units.

For the optimisation model, regardless of the total stock amount available, the optimised stock allocation results in higher net revenue than under the historical stock allocation. In fact, in some cases historical stock allocation results in losses (i.e., negative net revenue like mango and sunflower oil at 15,000 units). This provides evidence to support our fundamental hypothesis that the higher the level of disaggregation in the forecasting of (promotional) demand and the allocation of (promotional) the greater will be the percentage volume uplift in sales and the greater will be the level of net (promotional) revenue.

5   Discussion

Previous researchers have highlighted the importance of targeting distinct customer segments when designing promotional strategies (Hsu et al., 2012). The results of this study provide further evidence to support this view. For both product categories (fresh and ambient) the promotional impacts were significantly different for the different socio-economic segments (up-market and price sensitive) and the results for fresh carrots show that consumers who are more interested in the product (high product penetration) are much more likely to respond to promotions than consumers who have limited interest (low product penetration). These results are important in their own right, as they provide empirical evidence of the heterogeneity of consumer demand and promotional impacts across different consumer segments. In addition, they constitute a distinguishing feature of the simulation and optimisation models, enabling the modelling to reflect more accurately the dynamics of the promotional cycle as it happens, as opposed to what we assume (Raju et al., 1995). Using customer segmentations that are consistent with commercial practice facilitates more accurate forecasts of promotional uplifts at the store level and establishes the scope for improvement based on disaggregated sales data that is available to the retail buyer and the supply base.

These results are consistent with the findings of Srinivasan and Anderson (1998), who identified the limitations of assessing promotional impacts for highly aggregated product categories. Specifically, the weather was identified as an important (exogenous) factor influencing promotional sales, particularly for products with seasonal demand

(Demirag, 2013). Carrots and mangos are both from the fresh produce category but the impact of promotions and the moderating role of the weather are distinctly different.

One of the research questions addressed in this research is the extent to which promotional impacts vary according to the characteristics of the store, and in particular the size of the store, as reflected in the retail format (extra, super, express). This is a gap in the literature highlighted by Bucklin and Gupta (1999), who advocated the use of store level data in promotional planning, to reflect the heterogeneity of store performance and shopping missions – family shopping missions in extra stores versus top-up shopping in convenience stores. The results of this study provide evidence of the need to account for different store characteristics when forecasting promotional uplifts (which impact stock levels and replenishment decisions), with significant differences in sales uplifts between the largest (extra) stores and the smallest (express) stores.

6 Conclusions

This research clearly shows that sales promotions are a complex interplay of demand and supply side factors and use of disaggregated demand data at critical decision-making stages in the promotional cycle has the potential to improve promotional effectiveness. It draws its strength from the use of supermarket loyalty card data for simulating demand and the use of semi-structured interviews with practitioners to understand existing processes and inform the model design for the determination of optimal stock, volume uplift and net sales revenue.

The stakeholder interviews revealed that suppliers make little or no use of detailed demand data in the design of promotional strategies and little effort is made to evaluate the impact of promotions, beyond the aggregate increase in short-term sales. Connecting demand and supply side through more effective (disaggregated) demand data has the potential to change the way suppliers engage with retailers and offset the imbalance of market power between supermarkets and suppliers by providing the latter with an effective voice at key stages in the promotional cycle.

7 Limitations and future recommendations

This research is based on one UK retailer and a small number of suppliers, whose approach to the design, planning and execution of promotions are unlikely to reflect that of all retailers and all suppliers. In addition, the data requirements for the simulation and optimisation process are considerable and the generation of the necessary data is extremely time-consuming, given the permutations of product type, shopper type and store format. This is a potential barrier to adoption, particularly amongst smaller suppliers who lack the necessary resources. In order to increase the generalisability of our findings, further studies should include a wider range of products across a broader range of categories and involve a wider sample of retailers and suppliers.

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