USING SUPERMARKET LOYALTY CARD DATA TO EXPLORE THE MODERATING IMPACT OF SHOPPER SEGMENTS ON PROMOTIONAL RESPONSE

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ABSTRACT

The aim of this paper is to show how supermarket loyalty card data from a panel of over 1.4 million shoppers can be used to analyse the effect of price promotions in a way which can bring significant advantages to retailers and manufacturers when making promotional decisions. The paper demonstrates the significant advantages that loyalty card data can bring to enhance our understanding of promotions, compared to traditional scanner and panel datasets. Regression analysis is used to compare the effects of different promotional mechanics upon different tiers of product across the fresh beef category in Tesco; using both scanner data and loyalty card data. The results show that using loyalty card data, which enables us to moderate for specific shopper characteristics, produces more statistically significant results and provides a more detailed picture of how promotions influence sales.

INTRODUCTION

The use of promotions in retailing has increased rapidly in recent times, yet more often than not promotions are being implemented with an inadequate understanding of which mechanisms are most effective, for which products and for which shopper segments (Felgate et al, 2011). Despite this growth in the use of promotions, particularly in the Fast Moving Consumer Goods (FMCG) sector, consideration of their impact and effectiveness amongst academics has been limited. It has been identified as an important area for future research, as has the greater use of supermarket panel data to provide insights into how different shoppers respond to price changes, including promotions (Grewal and Levy, 2009). Moreau et al (2001) assert that a lack of understanding by retailers about consumer
perceptions of promotions can lead to weaknesses in their marketing strategies. Thus, as the use of promotions continues to grow, it is increasingly important to gain a more complete understanding of how consumers actually behave in response to different promotional activities.

This paper reports the use of loyalty card data from one of the biggest retailers in the world – Tesco - to analyse the impact of promotions. The aim of the paper is to demonstrate how such data can bring significant benefits to retailers and manufacturers when deciding promotional strategies, over and above traditional scanner datasets, which the majority of existing research is based around. While the case study is based on data from the UK, it demonstrates how other major retailers with similar loyalty card schemes (e.g. Kroger in the USA, and Casino in France) could make use of this powerful source of behaviour data to gain a better understanding of the effectiveness of promotions in key (destination) categories. The research also demonstrates the merits of implementing a loyalty card for those retailers who do not currently have such a scheme in place. The paper also contributes to the existing promotions literature, through presenting a conceptual framework to test the moderating effect of shopper specific characteristics such as life-stage and region on promotional impacts.

The paper is in four sections. The next section will provide some background to the research, including an overview of the existing literature in the area of promotions. Following this, the conceptual framework and hypotheses are presented. Next the methodology, data description and the results are described, followed by our conclusions, limitations and areas for further research.

Promotions

Drawing upon the definitions put forward from previous researchers (e.g. Webster 1971; Kotler 1988; Blattberg and Neslin 1990) promotions are defined as marketing events limited in duration, implemented to directly influence the purchasing actions of customers with the underlying intention of achieving the objectives set out in the marketing strategy for the retailer and/or manufacturer. These objectives may include improving competitive position, brand extension, category expansion or increasing profitability.
The use of price promotions in the UK has increased significantly over the last decade, particularly in grocery retailing where competition between retailers has intensified. In May 2009 a record 32 percent of all grocery sales in the UK were made up of products on promotion (Nielsen Wire 2009a). In the US the figure was even higher, with a reported 42.8 percent of grocery sales made on promotion in September 2009, up from 40.8 percent in 2008 (Nielsen Wire 2009b). This has resulted in both UK supermarkets and their (branded) suppliers becoming increasingly dependent on promotional activity to drive sales growth. It is our contention that much (if not most) of this activity has occurred with limited analysis (and thus understanding) of the impact of promotional activity beyond the uplift in sales of the promoted products.

Over the last few decades substantial inroads have been made in empirical research into the effects of price promotions and what influences their effectiveness. Previous studies have investigated the potential effects of promotions, including brand switching, category expansion and purchase acceleration (E.g. Chintagunta 1993; Manning and Sprott 2007; Martinez-Ruiz et al 2008). However, the vast majority of these studies have relied upon small scale scanner or panel datasets and small-scale experiments which many would argue cannot be considered representative of supermarket shoppers as a whole.

In terms of profitability, retailers will not necessarily see any tangible benefit where a promotion simply transfers sales from one brand to another, whereas a manufacturer will benefit if a promotion on their brand increases their sales at the expense of other brands. Retailers’ profits are dependent upon sales of both promoted and non-promoted brands so will reap the most benefit where a promotion attracts new customers and drives category sales. Indeed, up until fairly recently promotions were considered simply a ‘zero-sum’ game, just shifting consumption from one brand to another, or one time period to another, therefore not benefiting retailers other than in generating footfall for their stores (Putsis and Dhar 2001). Ideally, if the objective of the promotion is to generate revenue, retailers should be seeking promotions which increase overall spend in store at the category level.
Reviewing the extant literature revealed factors which can influence how effective promotions are, including:

- The type of promotional mechanic used (e.g. Manning and Sprott 2007)
- The length of promotions (e.g. Blattberg and Wisniewski 1987)
- The price/quality tier of the brand – shoppers respond differently to promotions on high priced (premium) brands compared to low price brands (e.g. Martinez-Ruiz et al 2008)
- The frequency of promotions (e.g. Mayhew and Winer 1992)
- Product specific characteristics such as perishability and bulkiness, or whether the product is utilitarian or hedonic (e.g. Wansink and Deshpandé 1994; Bell et al 1999; Delgado-Ballester and Palazon-Vidal 2005)
- Characteristics related specifically to the shopper, including household life-stage and location (e.g. Inman and Winer 1998)

Some of the above factors can be taken into account when analysing promotions using scanner data, such as the mechanic used, the length and frequency of the promotion and product specific characteristics. However, unlike loyalty card data, scanner data cannot moderate for shopper specific characteristics such as household size or lifestyle. This is because scanner data is aggregated to either store or retail chain level, and the sales cannot be attributed to specific shopper segments.

Consumers are heterogeneous in terms of their tastes, preferences and circumstances, and these are likely to shape their shopping behaviour ref?. In recent years a handful of studies have tried to identify the characteristics specific to those households that are most responsive to price promotions (e.g. Blattberg et al. 1978, Urbany et al. 1996, Ainslie and Rossi 1998, Inman and Winer 1998, Bawa and Gosh 1999). In these studies, several factors have been identified as potentially affecting promotional response, including demographic factors such as income, age, education level and employment status. For example, through qualitative studies there is consistent evidence of a positive relationship between promotional response and household size (Ainslie and Rossi 1998, Inman and Winer 1998, and Bawa and Gosh 1999). The more members there are in a household, the
further the shopping budget needs to stretch and hence the greater the promotional impact. The presence of young children was also found to increase the take-up of promotional offers, perhaps since the parents may have less time to shop and rely more on impulse purchases (Blattberg et al. 1978, Urbany et al. 1996). The disadvantage with most of these studies is that they were based around either small scale panel data or qualitative surveys using small, unrepresentative samples of shoppers.

**Conceptual Framework**

The literature review revealed a significant gap in the existing promotions literature which we contend can only be addressed through the analysis of loyalty card datasets. Current evaluations of promotions are mostly based on point of sale scanner data which, unlike loyalty card data, cannot be moderated for differences between shopper segments. Scanner data can tell us what is being purchased, but only loyalty card data can tell us who is buying it on a large scale. Our proposed conceptual framework for measuring the impact of promotions on sales in this research is described in Figure 1. The framework theorises that sales per store are a function of promotion, with shopper specific characteristics acting as moderator variables. These characteristics will vary, but in practice form the basis of segmentation strategies for targeted promotions. Thus, they will include factors such as life-stage, life-style, geo-demographics and TV advertising region.

(Figure 1 Here)

Distribution is also accounted for in our framework since sales per store is used as the dependent variable rather than total sales. This is because if the number of stores change over a time period (as is the case with growing retail chains) this will affect the sales at aggregate level, when measuring sales over time. Moreover, promotional strategies often include increased distribution as part of the promotional mix, securing maximum promotional uplift through increased availability.
Different price promotion mechanics are the independent variables, upon which sales per store are dependent. These include price cuts and multi-buy promotions. Promotional impacts are moderated by two shopper profiling variables: shopper life-stage and TV advertising region. Previous studies have indicated that both household composition (Urbany et al. 1996, Ainslie and Rossi 1998, Inman and Winer 1998, and Bawa and Gosh 1999) and geographical location (Lodish 2007) can impact on promotional response. The loyalty card data used for this research includes segmentation for both of these characteristics.

Based on the conceptual framework, the following hypotheses are posited:

\[ H1: \text{Promotional impacts are moderated for by the life-stage profile of the shopper} \]

\[ H2: \text{Promotional impacts are moderated for by the geographical location of the shopper} \]

In order to test the above hypotheses, the promotional impact on sales will be measured using both a scanner data set and a loyalty card dataset. The next section will describe in detail the methodology and data used to test these hypotheses.

**METHOD**

Multiple regression was used to estimate the impact of different promotional mechanics on sales. Multiple regression enables us to evaluate the separate contributions of one or more variables acting jointly on a single dependant variable. Moreover, it is applicable to the analysis of promotions as a given product may use several types of promotion, each of which may have a different effect on sales of both the promoted product and substitute products. Regression analysis techniques have been widely used by other researchers to estimate the effects of promotions (see e.g. Bolton 1989; Sethuraman and Tellis 2002; Macé and Neslin 2004; Van Heerde et al 2004). Regression analysis is
well suited to the analysis of large samples of data and for measuring the effects efficiently across different product sub-groups; identifying switching and substitution effects between products and differences across segments of shoppers ref??.

The Model

A multiple regression model was estimated to analyse both the scanner and loyalty card data. The following equation represents the model used for the regression analysis:

$$SALES_{PER\_STORE_{it}} = \beta_0 + \beta_1 PROMO_{it1} + \beta_2 LIFESTAGE_{it2} + \beta_3 REGION_{it3} + e_{it}$$

In the model, $SALES_{PER\_STORE_{it}}$ represents the dependant variable sales value per store for a given product sub-group, $i$, in a given time period, $t$. The parameters of the model are $\beta_0$, which represents a fixed constant, $\beta_1$ which represents 0-1 dummy variables for the different types of price promotion for product sub-group $i$ in the time period $t$, $\beta_2$ which moderates for different shopper life-stage segments and $\beta_3$ which moderates for different UK regions. The promotion variable ($\beta_1$) captures four different types of promotion used in the fresh beef category: small price reductions of less than fifteen per cent off, medium price reductions of between fifteen to thirty per cent off, large price reductions of more than thirty per cent off the original price and multi-buy promotions. The error term, $e$, incorporates all the immeasurable factors which may also be influencing sales aside from promotions.

Data

There are two main types of data used in the promotions literature to analyse the impact of promotions on purchasing behaviour: panel data and retailer scanner data. Panel data provides information at an individual household (or segment) level; for example by household size or by age.
Popular sources of panel data include A. C. Nielsen and TNS Worldpanel. Examples of studies which have utilised panel data include Chintagunta (1993), Bell et al.(1999), and Ailawadi et al (2007). All these studies suffer from the same limitation in that the panel data used is relatively small scale and therefore less representative of the whole population when trying to make inferences about the way people respond to promotions.

Store-level scanner data pools all sales in a given store, or chain of stores over a period of time but does not contain information on specifically which type of household these sales relate to. Examples of studies which have incorporated store-level scanner data include Raju (1992), Macé and Neslin (2004), and Martínez-Ruiz et al. (2006b). Panel data is more detailed than store-level scanner data and can be more useful in many circumstances, for example to compare the effects of promotions on different categories of shoppers or on brand loyalty. However, panel data can be ‘noisier’ than aggregate store-level data because in panel data sales will typically be generated from a smaller sample size of consumers, which is likely to result in more week to week variation. The lower noise in aggregate store sales data is a strong factor in favour of using it for many types of analysis. Store-level scanner data also has the advantage of containing a much larger sample than panel data, meaning there will be less variation in the sales data which should yield more robust results.

Using loyalty card data for analysis has the advantage that it can be disaggregated down beyond the ‘total sales’ level (e.g. to sales by shopper segment and region), providing more data points to analyse and reducing the amount of noise that is prevalent in highly aggregated data. Loyalty card data combines both the advantages of scanner and panel data, in that the data is collected on a relatively large scale (in the case of large retail chains) and can be segmented to show who is buying what.

This paper uses both an aggregated scanner data set and a loyalty card data set in order to test the hypothesis that promotional impacts are moderated by demographic characteristics of the shopper. The same model is applied to both data sets to analyse the impact of promotional mechanics on sales. Both datasets cover the same time period (86 weeks from 29th May 2006 to 21st January 2008).
product category (fresh beef) and supermarket chain (Tesco). The scanner dataset contains the total aggregate sales for fresh beef products in Tesco, whereas the loyalty card dataset includes purchases made using the Tesco ClubCard (approximately 80% of total transactions), and is segmented by shopper household life-stage and region.

The Tesco ClubCard was launched in 1995, and is currently used by over 14 million households in the UK (approximately 40 percent of all UK households). The ClubCard provides data not only on what is being sold on a national basis but also who is buying it, with shoppers segmented by television advertising region, life-stage, life-style (Tesco have their own life-style segmentation based on the distribution of products in a shopper’s basket over a twelve week period) and geo-demographics. Tesco is the largest grocery retailer in the UK, with a segmented retail strategy, serving the entire spectrum of shoppers from price sensitive to up-market, and through different retail formats such as on-line, convenience and supermarkets. Recent figures indicate Tesco’s market share to be at 30.7 percent of total grocery retailing in the UK (source: Kantar Worldpanel 2010).

The power of using retailer loyalty card data is the ability to generate purchasing data at a segmented level on a large scale. For the purposes of this research the loyalty card data was used to create a cross-sectional panel data set, with sales data sorted by shopper life-stage and TV advertising region. Within the dunnhumby database there are five life-stage segments and ten TV advertising regions, which made it possible to create a panel dataset based on fifty individual segments in total. The different life-stage segments are young families (all children under 10yrs), older families (at least one child over 10yrs), young adults (aged 20-39yrs), older adults (aged 40-59yrs) and pensioners. The different regions of the UK, used within the panel dataset, were Scotland, Wales and the West, the South West, the South East, the Midlands, East England, London, Yorkshire, the North East and the North West. In order to offset the effect caused by increases in distribution (due to the continued growth in Tesco stores) the sales value was divided by the number of stores selling the product each week. This created the dependant variable; sales value per store.
The dataset comprised of weekly sales over an 86 week period from 29th May 2006 to 21st January 2008. This time period was used because it was the longest uninterrupted time period for which complete promotional information was available for both the scanner and loyalty card datasets analysed. It was felt a longer time period as possible should be used because it enables more promotions to be included for each product then would be possible with a shorter time frame, and in turn this allows for more robust assumptions to be made as to which promotions work best for which products.

The example used in this paper is fresh meat – a key destination category for most supermarket chains, with a particular emphasis on the fresh beef sector. Fresh meat was chosen because it is a high penetration product category in the UK, with household penetration over 70% for fresh meat, and 65% for beef alone (Source: Dunnhumby, 2011). In the UK, the majority of fresh meat sold through supermarkets is private label with little or no branding, making it unique from most non-commodity product categories. In other grocery categories where branding is more prevalent, consumer attitudes towards private label promotions may differ from the fresh meat sector. While there is no branding, as such, within the fresh meat sector in the UK, products are positioned differently with a range of price/quality tiers, from value products through to premium and organic. These different price/quality tiers of products can be considered in essence to be separate ‘brands’ and the model enables us to identify switching effects between these different ‘brands’ of beef. Sharp (2010) asserts that consumers are well aware of this price/quality tier system and respond differently to low-end and premium-end promotions.

As well as different tiers there are also different cuts such as roasting joints, ground beef, and steaks. For the data analysis individual beef stock keeping units (SKUs) were grouped into eleven subgroups categorised by cut, and by tier. The products were first sorted by cut: roasting joints, frying and grilling meats such as steaks and chops, and ground beef. These groups were then further disaggregated by price/quality ‘tier’: standard label (e.g. Tesco private label brand), premium (e.g. Tesco Finest brand), organic, value (e.g. Tesco Value) and healthy label (e.g. lean or Tesco Healthy Living range). Substitution is most likely between the different tiers (e.g. Organic, Standard) of the
same cut (e.g. Roasting joints), rather than between different cuts, therefore the analysis was carried out within the different cuts of meat. Roasting joints were analysed together, as were fry/grilling beef and ground beef. This made it possible to observe switching effects of promotions between tiers of products, within each cut sub-category. For example, a promotion on standard roasting beef joints may influence sales of value roasting beef joints. Substitution between cuts is considered less likely since different cuts are used for different meal occasions.

While the results for a specific product category (fresh beef) cannot be directly applied to other commodities, it is thought the model used can be adapted and applied to most product categories in order to help retailers and food manufacturers make better (more informed) decisions with regard to promotional planning. However, further empirical research will be required to support the notion that the model could be applied to other categories.

RESULTS AND DISCUSSION

In total 24.4 percent of fresh beef sales occurred while promotions were taking place during the time period analysed. Table 1 shows the percentage of sales within the different beef sub-groups occurring while on promotion. These percentages were calculated by summing the sales of each individual product within each sub-group during the weeks when a promotion was taking place on the given product, and then diving this by the total sales for each product.

(Table 1 Here)

In total almost 40 percent of roasting beef sales occurred while products were on promotion, compared with 39 percent for ground beef and a much lower value of 16.7 percent for fry/grilling beef. Within the roasting and ground categories the highest percentage of sales on promotion occurred within the standard sub-group, yet for the fry/grilling beef category the highest percentage of sales on promotion occurred within the premium sub-group. These figures in Table 1 reflect the fact that some
categories are more heavily promoted than others. Standard tier promotions occur almost on a weekly basis for all cuts of beef, whereas organic and value promotions are generally much less frequent.

The results of the regression analysis will now be presented for both the scanner and loyalty card datasets, with only those results which are significant at least at the 5 percent significance level being reported.

**Category Level Results**

Table 2a reports the results of the regression analysis at the total (fresh beef) category level for the aggregated scanner dataset, while Table 2b shows the same for the loyalty card dataset. The tables show the percentage uplift in sales resulting from different promotional mechanics for the total beef category, and subdivided for the roasting, ground and fry/grilling beef subgroups.

It can be seen that the analysis using the scanner dataset produces fewer statistically significant results, compared to the loyalty card dataset. This indicates that the scanner data is too highly aggregated to be able to observe the impacts of specific promotions, when looking at category level data. The loyalty card dataset includes more data points, since it is based on a panel of 50 different shopper segments (by life-stage and region), and therefore more statistically significant promotional impacts were picked up using the regression analysis.

*(Tables 2a and 2b Here)*

The r-squared values for the analysis using scanner data were also lower than for the loyalty card data set. For example, within the roasting beef sub-group promotions were found to explain 3% of the variance in sales for roasting beef through scanner data, and hence there were no promotions that had a statistically significant impact on sales. In contrast, promotions were found to explain 13%
of the variance in sales using the loyalty card data and both large price cuts and multi-buy promotions had a statistically significant impact on sales.

If scanner data alone had been used for this analysis, at the category level it would be assumed that only medium price cuts had a statistically significant effect on sales at the total category level. It would appear, when drilling down to cut level, that promotions only had an effect on sales of fry/grilling beef; with medium price cuts creating a sales uplift of 12.7%. However, looking at the results from the loyalty card data analysis, more relationships between sales and promotions are observed.

Looking specifically at the results from the loyalty card analysis (Table 2b) it can be inferred that promotions account for 14% of the variance in sales of beef at the category level, which tells us that promotions are one of several factors likely to be influencing sales. At the total category level the impact of promotions overall was found to be insignificant, however when divided into specific promotional mechanics, it can be seen that multi-buys resulted increased sales for the fresh beef category while medium price cuts had the opposite effect. This result is important as it shows that not all promotions generate increased sales revenue for the retailer, and indicates that it would be highly beneficial for retailers to make informed decisions when deciding promotional plans. However, this result does not necessarily mean multi-buys are the best promotion to use for all fresh beef products.

From the loyalty card data analysis, it can be seen that promotions have the biggest influence on sales within the fry/grilling beef category, since the R-Squared value tells us 38 percent of the variance in sales is attributable to promotions. Within the roasting category, large price cuts were found to have the greatest significant positive impact on sales value, indicating that sales value (per store) will increase by 0.2% during the promotion. Within the ground beef category multi-buys were the only promotion to have a significant impact overall, while medium price cuts were the only promotion to have a significant impact on fry/grilling beef sales. Small price cuts did not have a significant impact on sales across any of the beef cuts. The results indicate that the promotional
impacts are affected by the mechanic used; whether it is a small price cut or a multi-buy promotion, the effect will not always be an uplift in sales value.

Disaggregated Results (by Price/Quality Tier)

Table 3a and Table 3b report the regression results for the ground beef price/quality tier subgroups with respect to different price promotions for scanner data and loyalty card data respectively. The purpose of this is to provide an example as to how promotional impact can vary between different ‘tiers’ (or ‘brands’) of the same product. Again there are significant differences between the analysis using the scanner data and that using the loyalty card data.

(Table 3a Here)

The analysis using scanner data produces fewer statistically significant results, however the results it does produce show there to be larger uplifts (or decreases) in sales than the loyalty card data. For example, the scanner dataset shows a multi-buy on healthy ground beef to generate a sales uplift of almost 4%, whereas the loyalty card data shows a smaller sales uplift of just 0.03%. The scanner dataset does not produce any statistically significant results for the most heavily promoted product category, standard ground beef. However, with the loyalty card dataset promotions account for 16% of the variance in sales of standard ground beef and several promotions were found to have an impact on sales.

(Table 3b Here)

The analysis using the loyalty card data enables us to observe more interactions between promotions and sales than using the scanner data. As a result there are several findings that can be noted. Within the ground beef sub-group promotions have the biggest impact in the healthy subgroup, where promotions account for 54 percent of the variance in sales. Multi-buy promotions on healthy ground beef have a significant positive effect on sales of healthy ground beef, but consumers will switch to organic when on promotion. Within the standard subgroup, multi-buy offers have a large
positive impact on sales, but consumers will switch from standard to premium when premium ground beef is on offer.

Sales of organic ground beef are negatively affected by promotions on standard and premium products. Harder to explain is the positive impact on premium ground beef of multi-buy promotions on healthy and standard ground beef. However it may be that consumers, who only want one unit of the product, switch to premium because they do not want to partake in the multi-buy promotions on healthy or standard ground beef that they otherwise would buy. This would therefore suggest that multi-buy offers have a negative impact on some shoppers, who will actively switch to a substitute product as a result. Similar affects are observed elsewhere in the sub-group, for example standard multi-buy promotions apparently increase sales of premium ground beef. The results indicate that promotional impacts do vary depending on the product being promoted, as well as the type of mechanic used, and that these are differences are more notable when analysing loyalty card data as opposed to scanner data.

Disaggregated Results by Shopper Type

The biggest advantage of using loyalty card data is that it enables us to identify how different segments of shoppers respond to promotions. Traditionally promotions have been limited to a ‘one size’ fits all approach, but understanding how the short-term response to price reductions and promotions varies across segments should be seen as important in the designing and targeting of effective promotions (Lim et al. 2005). This is something which cannot be achieved through using scanner data alone since the data is highly aggregated. Loyalty card data can be segmented in several ways, including by life-stage and region. Here the results by life-stage are presented, but the same segmented analysis is possible for other segmentations, including by shopper region.

Table 4 reports the results of the regression analysis using loyalty card data, again just for ground beef as an example, by life-stage segment with respect to the various promotions.
It can be seen that standard multi-buy promotions had a large and positive effect on sales of standard ground beef within all segments except Pensioners. The segment for which sales value increased the most in response to the standard ground beef multi-buy promotion was young families. Similarly the young families were the segment for which sales of standard ground beef fell the furthest in response to the price promotions on premium ground beef. Sales value of standard ground beef amongst both older adults and pensioners actually increased in response to multi-buy promotions on healthy ground beef. This indicates that shoppers within these segments were put off by the multi-buy offer on healthy ground beef, which perhaps they normally purchase, and instead switched to buying standard ground beef. Older adults and pensioners perhaps do not want to purchase multiple packs of ground beef since they do not have families to feed, so switch their spend to a product not on offer. It can be seen that there are differences in the response amongst different households, which again may vary between products and commodities or due to the mechanic used.

CONCLUSIONS

The main purpose of this paper was to demonstrate that supermarket loyalty card data can be used to generate unique empirical insights into understanding the effectiveness of promotions. Existing research looking at the impacts of promotions has mainly been based around scanner datasets which are usually highly aggregated and it is our argument that as a result much of the impact of promotions on sales is not being captured. Through analysing two datasets, this paper has demonstrated that more insight into the promotional impacts on sales can be gained from loyalty card data than scanner data. The scanner dataset produced far fewer statistically significant results than the loyalty card data because the data is so highly aggregated. In being able to moderate for specific shopper demographic segments, the loyalty card data analysis was able to provide us with more
insight into what happens when different products are promoted. In addition, the loyalty card data also enabled us to see the differences between shopper segments in their response to promotions.

One of the main findings from this paper is that there is considerable variability in the impact of different promotion mechanics between and within the different sub-groups, many of which would not have been observed with scanner data. This illustrates the point that one promotion does not fit all and promotional strategies should take greater notice of the effectiveness at the individual product level, to avoid devaluing the product category. In the example used for this paper, there were found to be differences in which promotions work best within each cut and price/quality tier within the beef category, which could not be captured by analysis of highly aggregated data. Much of the promotional research, not just in the meat category, has used highly aggregated data on product categories to measure promotional impacts where in fact very different results may have been observed if the data used had been at a more disaggregated level.

The research has also demonstrated how promotional response varies across life-stage segments. Generally spend amongst families increased the most in response to promotions, and for pensioners the least. This result is perhaps unsurprising, but some interesting points have arisen. For example pensioners and older adults appear to be put off multi-buy promotions within the ground beef category, to the extent that they switch their purchases to standard ground beef in response to multi-buy offers on healthy ground beef. Further research across other grocery categories using panel data is necessary for retailers to have a broad understanding as to how different segments respond to enable them to plan and target promotions more effectively.

The findings in this paper have also contributed further to the promotions literature on brand switching. Existing literature is unanimous in the belief that if a lower price/quality tier brand is promoted it does not attract customers from high-tier brands, but the promotion of higher quality, premium priced brands impacts significantly upon weaker brands (see e.g. Mulhern and Leone 1991; Martínez-Ruiz et al. 2006a). While the results from the ground beef sub-group backed up this theory with sales of standard ground beef falling considerably in response to promotions on premium ground
beef, some other results were conflicting. For example, while medium price cuts on premium roasting beef were found to have a significant negative impact on sales of standard and value beef, there was evidence of consumers trading down from premium tier products as a result of large price cuts and multi-buy offers on standard roasting beef. These findings suggest that while the theory of asymmetric switching can be applied in some circumstances, it does not apply for all products categories.

The main academic contribution of this paper is methodological rather than theoretical. The findings contribute to and enhance our existing knowledge of promotions through analysing the impacts using a data set unique in both its size and scope, and which has not previously been used for such a purpose. Loyalty card panel data is now more accessible than ever to many of the major retailers, but so far it is not being used to the best of its potential to inform decision making as to which promotions will be most effective. As can be seen from the results, some promotions have a greater impact than others, but retailers need to understand these differences in order to implement promotions effectively. There is much scope to expand upon this research through adding additional variables to the model, such as seasonality and merchandising, as well as using other product categories, and incorporating more shopper demographic variables.

The use of loyalty card schemes amongst retailers worldwide is increasing, which means more detailed analysis of promotional impacts, of the kind reported here is becoming increasingly possible. Retailers and manufacturers need to move away from the notion that one promotion fits all and instead focus their efforts on targeting promotions effectively and using those mechanisms which will yield the best results for the particular product or category in question. This research demonstrates the value of implementing a loyalty card scheme to those retail chains which do not yet have one. Loyalty card schemes do not just offer rewards to the shopper; they can be an invaluable tool in providing data to significantly contribute to our understanding of marketing issues, including promotions.

LIMITATIONS AND AREAS FOR FURTHER RESEARCH
There are limitations to the research presented in this paper. The analysis only looks at one product category, within one retailer and only includes a limited number of independent variables within the model. Factors which can impact upon sales aside from promotions include seasonality, advertising, merchandising and information on point of sale displays. All such factors are also likely to impact upon how effective promotions are. Following on from this study, further research can be carried out to look at more product categories and to include more variables to see how this affects the results and demonstrate whether this further strengthens the case for using loyalty card data for such analysis.

FIGURES

*Figure 1: Conceptual Framework for measuring the Impact of Promotions on Sales*

![Conceptual Framework for measuring the Impact of Promotions on Sales](image)

TABLES

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Table 1: Percentage of Sales occurring on Promotion by Beef Sub-group over the 86 Week period from 29th May 2006 to 21st January 2008

<table>
<thead>
<tr>
<th>Sub-group</th>
<th>% Of Sales Occurring On Promotion</th>
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<tbody>
<tr>
<td></td>
<td>Roasting Beef</td>
</tr>
<tr>
<td>Total</td>
<td>39.96%</td>
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<tr>
<td>Standard</td>
<td>50.31%</td>
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<tr>
<td>Premium</td>
<td>27.88%</td>
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<tr>
<td>Organic</td>
<td>31.71%</td>
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<td>Healthy</td>
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<tr>
<td>Value</td>
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Table 2a: Regression results, using Scanner Data, for the fresh beef category with respect to different Promotional Mechanisms

<table>
<thead>
<tr>
<th>Promotion</th>
<th>Uplift in Sales (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Total Beef Category</td>
</tr>
<tr>
<td>Small Price Cut (&lt;15%)</td>
<td></td>
</tr>
<tr>
<td>Medium Price Cut (15-30%)</td>
<td>-8.12**</td>
</tr>
<tr>
<td>Large Price Cut (&gt;30%)</td>
<td></td>
</tr>
<tr>
<td>Multi-Buy</td>
<td></td>
</tr>
<tr>
<td>R-Sq</td>
<td>0.1302</td>
</tr>
</tbody>
</table>

**p<0.01   *p<0.05

Table 2b: Regression results, using Loyalty Card data, for the fresh beef category with respect to different Promotional Mechanisms

<table>
<thead>
<tr>
<th>Promotion</th>
<th>Uplift in Sales (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Total Beef Category</td>
</tr>
<tr>
<td>Small Price Cut (&lt;15%)</td>
<td></td>
</tr>
<tr>
<td>Medium Price Cut (15-30%)</td>
<td>-7.18**</td>
</tr>
<tr>
<td>Large Price Cut (&gt;30%)</td>
<td></td>
</tr>
<tr>
<td>Multi-buy</td>
<td></td>
</tr>
<tr>
<td>R-Sq</td>
<td>0.1437</td>
</tr>
</tbody>
</table>

**p<0.01   *p<0.05
Table 3a: Regression Results, using Scanner Data, for the Ground Beef sub-groups with respect to different Price Promotions within the Ground beef category

<table>
<thead>
<tr>
<th>Promotion</th>
<th>Standard Ground Beef</th>
<th>Premium Ground Beef</th>
<th>Organic Ground Beef</th>
<th>Healthy Ground Beef</th>
</tr>
</thead>
<tbody>
<tr>
<td>Premium - Medium Price Cut</td>
<td></td>
<td>0.89**</td>
<td>-1.97*</td>
<td></td>
</tr>
<tr>
<td>Healthy - Multi-buy</td>
<td>0.60*</td>
<td></td>
<td></td>
<td>3.97**</td>
</tr>
<tr>
<td>Organic - Multi-buy</td>
<td>-1.50*</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Standard - Multi-buy</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>R-Sq</td>
<td>0.0684</td>
<td>0.3661</td>
<td>0.1148</td>
<td>0.4066</td>
</tr>
</tbody>
</table>

**p<0.01   *p<0.05

Table 3b: Regression Results, using Loyalty Card Data, for the Ground Beef sub-groups with respect to different Price Promotions within the Ground beef category

<table>
<thead>
<tr>
<th>Promotion</th>
<th>Standard Ground Beef</th>
<th>Premium Ground Beef</th>
<th>Organic Ground Beef</th>
<th>Healthy Ground Beef</th>
</tr>
</thead>
<tbody>
<tr>
<td>Premium - Medium Price Cut</td>
<td>-0.06*</td>
<td>0.019*</td>
<td>-0.077*</td>
<td></td>
</tr>
<tr>
<td>Healthy - Multi-buy</td>
<td>0.032*</td>
<td>0.0197*</td>
<td>0.05*</td>
<td>0.0349**</td>
</tr>
<tr>
<td>Organic - Multi-buy</td>
<td>0.07**</td>
<td>0.017**</td>
<td>0.09**</td>
<td>-0.09**</td>
</tr>
<tr>
<td>Standard - Multi-buy</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>R-Sq</td>
<td>0.164</td>
<td>0.26</td>
<td>0.113</td>
<td>0.544</td>
</tr>
</tbody>
</table>

**p<0.01   *p<0.05

Table 4: Regression Results, using Loyalty Card Data, by Consumer Life-stage for the Standard Ground Beef sub-group

<table>
<thead>
<tr>
<th>Promotion</th>
<th>Older Adults</th>
<th>Young Adults</th>
<th>Older Families</th>
<th>Young Families</th>
<th>Pensioners</th>
</tr>
</thead>
<tbody>
<tr>
<td>Premium - Medium Price Cut</td>
<td>-0.2**</td>
<td>-0.41**</td>
<td>-0.62**</td>
<td>-0.09**</td>
<td></td>
</tr>
<tr>
<td>Healthy - Multi-buy</td>
<td>0.023**</td>
<td></td>
<td></td>
<td></td>
<td>0.113**</td>
</tr>
<tr>
<td>Standard - Multi-buy</td>
<td>0.231**</td>
<td>0.34**</td>
<td>0.51**</td>
<td>0.616**</td>
<td></td>
</tr>
<tr>
<td>R-Sq</td>
<td>0.1419</td>
<td>0.1282</td>
<td>0.1263</td>
<td>0.1332</td>
<td>0.1021</td>
</tr>
</tbody>
</table>

** * p<.01 * p<.05
REFERENCES


