Retail & Marketing Analytics

Individual Assignment

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Contents

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Introduction

In today's data-driven business world, we rely on historical data to understand existing strategies and make informed decisions. Likewise, we can examine various marketing elements, such as in-store promotions and pricing strategies, to understand their impacts on performance metrics such as sales. To do so, one can employ marketing mix modelling (MMM) techniques to uncover the relationship between marketing elements and performance metrics. One of the most well-known models to estimate the impacts of various promotion strategies on sales is the SCAN*PRO model. With this model, we can evaluate different marketing scenarios and optimise their marketing spend to achieve better results.

In this report, we will focus on evaluating the effects of display promotion, feature advertising and temporary price cuts on the sales of mouthwash products from a particular store in Cincinnati, Ohio using the SCAN*PRO model. The report will start with explorations of the aggregate data across stores and product categories to get a sense of the performances and marketing mix effects at a high level. We will then proceed by performing a deep-dive analysis into a specific store and category using the SCAN*PRO model to evaluate the marketing mix elements. Finally, we will discuss the limitations and potential improvements to extend the analysis.

Dataset

The dataset used is a real-world data named "Breakfast at the Frat", retrieved from dunnhumby Source File. It contains 156-week sales data and promotion information of the top five products in four categories: 1) Oral hygiene, 2) Bag snacks, 3) Frozen pizza and 4) Cold cereal, across stores in four states in the U.S.: 1) Illinois, 2) Kentucky,

3) Ohio and 4) Texas. In total, there are 57 unique products recorded identified from their UPCs and 17 unique brands across all 4 categories and 79 stores.

The main variables that we will be using are “UNITS” which gives the weekly sales, “PRICE”, “FEATURE” and “DISPLAY” which indicate the marketing strategy used. The full variables available in the dataset can be found in table 1 below.

Table 1. Glossary of variables found in the dataset

VARIABLE NAME	TABLE	DESCRIPTION
ADDRESS_CITY_NAME	Store	City
ADDRESS_STATE_PROV_CODE	Store	State
AVG_WEEKLY_BASKETS	Store	Average weekly baskets sold in the store
MSA_CODE	Store	(Metropolitan Statistical Area) Geographic region with a high core population density and close economic ties throughout the surrounding areas
PARKING_SPACE_QTY	Store	Number of parking spaces in the store parking lot
SALES_AREA_SIZE_NUM	Store	Square footage of store
STORE_APPEAL	Store	Retailer's designated store appeal
MANUFACTURER	Products	Manufacturer of product (or brand)
CATEGORY	Products	Category of product
DESCRIPTION	Products	Product name or description
BASE_PRICE	Data	Base price of item
DISPLAY	Data	Product was a part of in-store promotional display
FEATURE	Data	Product was in in-store circular
HHS	Data	Number of purchasing households
PRICE	Data	Actual amount charged for the product at shelf
WEEK_END_DATE	Data	Week ending date
SPEND	Data	Total amount spent (i.e., $ sales)
STORE_NUM	Data, Store	Store number
SUB_CATEGORY	Products	Sub-category of product
TPR_ONLY	Data	Temporary price reduction only (i.e., shelf tag only, product was reduced in price but not on display or in an advertisment)
UNITS	Data	Units sold
UPC	Data, Products	(Universal Product Code) Product specific identifier
VISITS	Data	Number of unique purchases (baskets) that included the product
PRODUCT_SIZE	Products	Package size or quantity of product

Data Explorations

Before jumping into the marketing mix model, we will perform exploratory data analysis as a preliminary step. Our focus in this step would be to understand the general pricing and promotion effectiveness at an aggregate level.

To start with, we will observe the price distributions of the products across brands and categories in figure 1. It is interesting to note that the brand "COLGATE" has a single point boxplot at $8 with outliers below that price point. This shows that "COLGATE" is rarely put under price cut promotion, even at aggregate level across all stores. Upon a deeper look into this, we find that the only product sold under "COLGATE" is a mini disposable toothbrush, comprising only 0.35% of all the sales recorded under "ORAL HYGIENE" category.

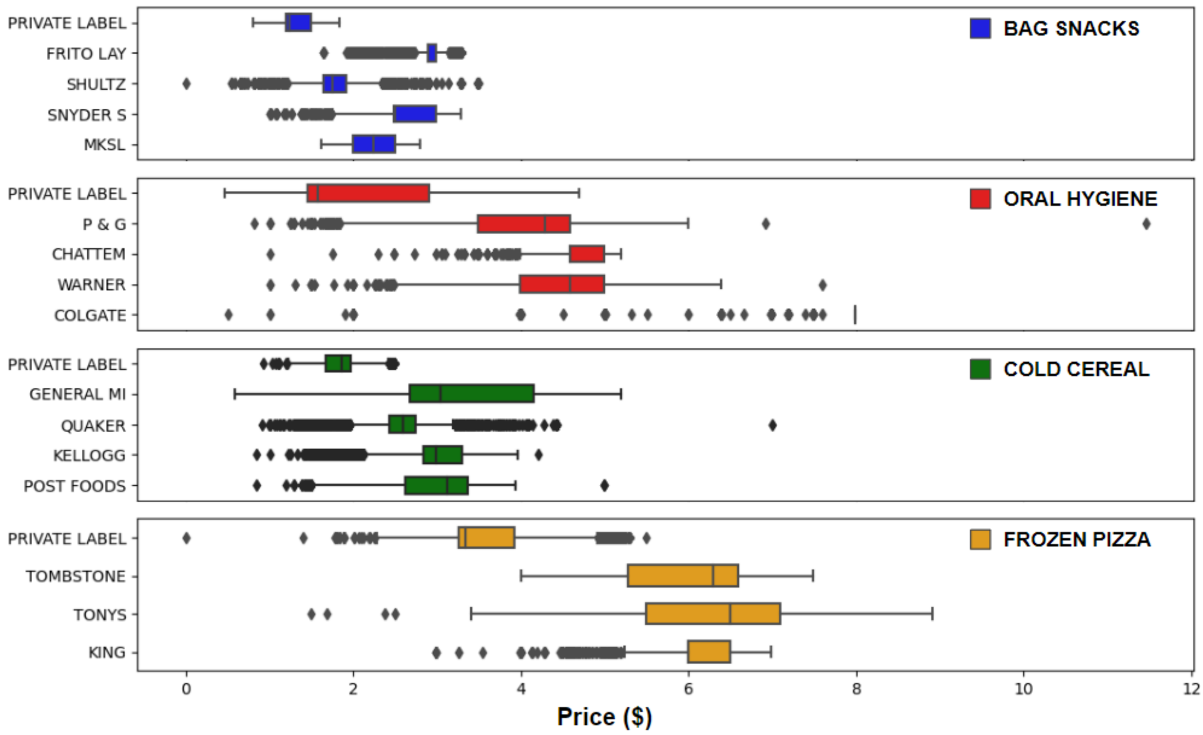

Figure 1. Boxplots of product prices of each brand in each category.

Now that we have observed the available price ranges in each category, we proceed to studying the effect of price cuts on sales performance. To do this, we first calculate the difference in each weekly sales observation from the average and then calculate the discount rate from the base retail price, “BASE PRICE”, for the respective observations. Next, we visualise the distribution of the observations using a heatmap by slicing the increase in sales and discount rates into bins as shown on figure 2 below.

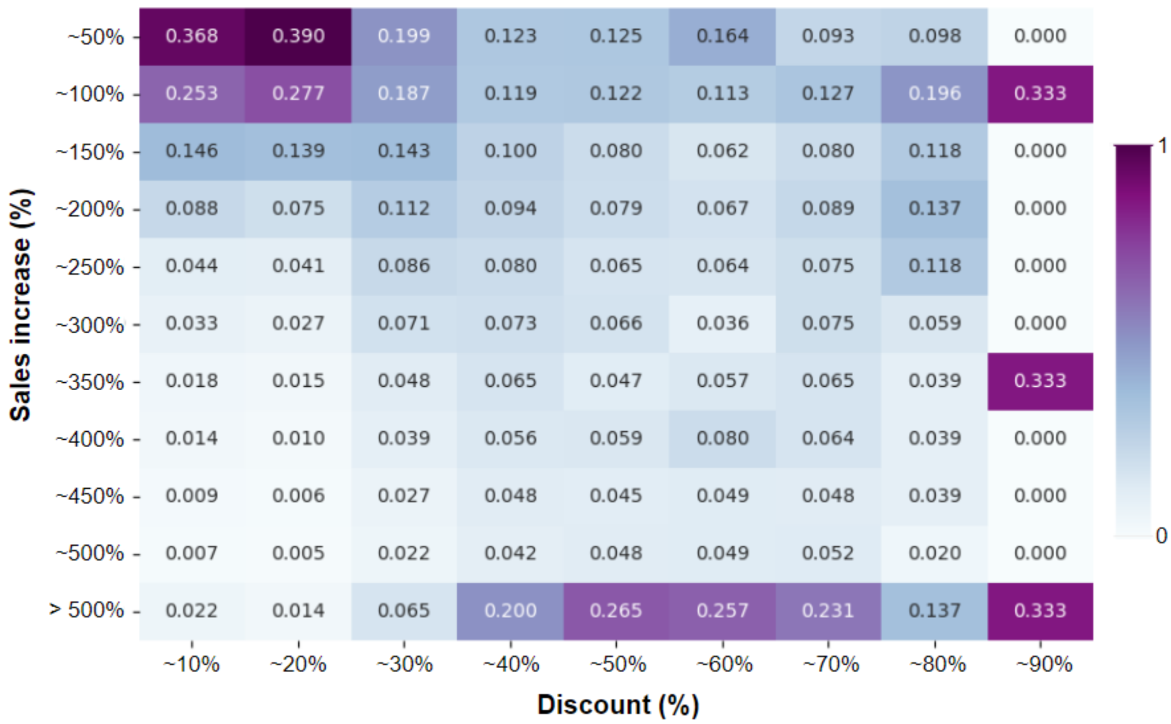

Figure 2. Distribution of proportion of sales increase by the discount rate applied.

Each column indicates a discount rate bin, for example, ~20% indicates a discount rate between 10% and 20% and it captures all the products that are discounted at this rate. Meanwhile, each row within the column indicates the proportion of the observations that experienced a certain percentage of sales increase. For example, the top row of the discount rate column ~20% shows that there are 0.390 or 39.0% of the observations with a discount rate between 10% to 20% experiencing up to a 50% increase in sales performance.

It appears that, on average, at discount rate up to 20%, approximately 62% to 67% of the time the sales went up by up to ~100%. However, once the price cut went to 50% and 60%, the increase in sales is significantly higher with around 26% of the time having more than 5x increase in sales. There may be a psychological effect in play affecting consumer's behaviour, as consumers may perceive a 20% off deal as just a decent discount, whereas a 50% off is a great deal causing a jump in sales.

Lastly, we study the effect of promotions and the lagged effect from the previous promotions on sales performance. To do so, we estimate the effect on sales using a heatmap as shown in figure 3 below.

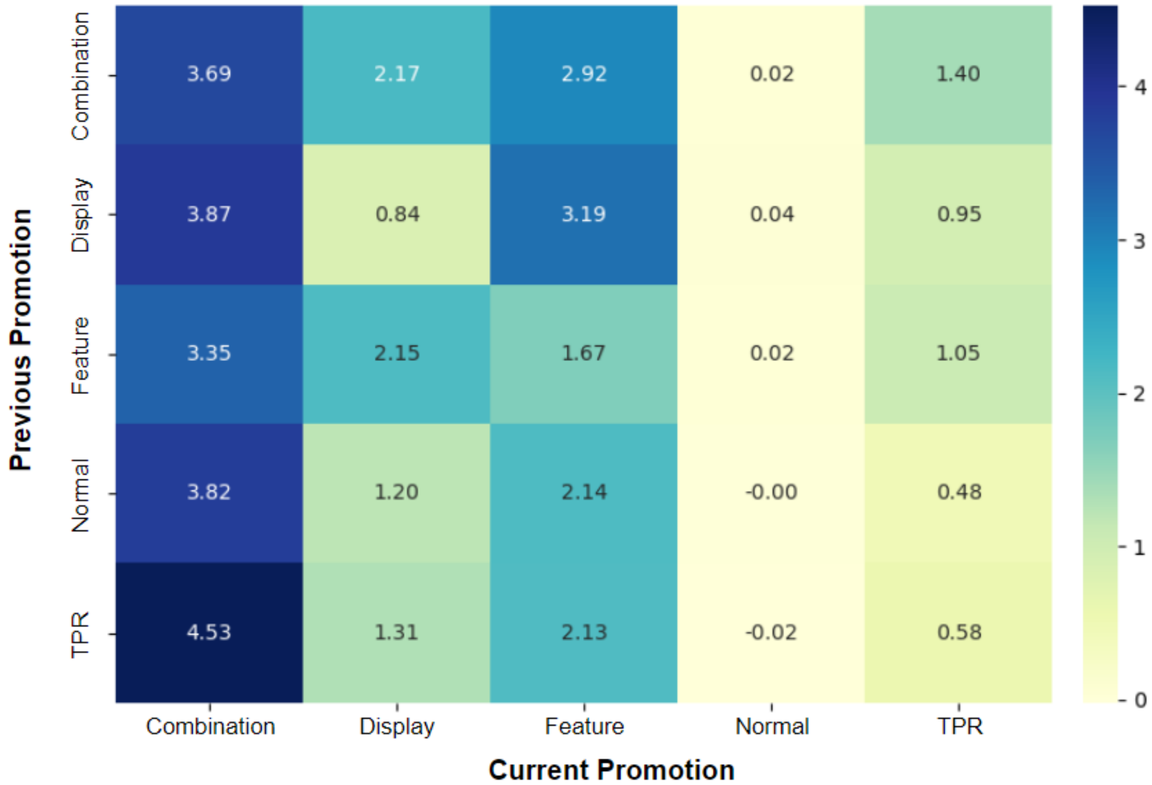

Figure 3. Heatmap of increase in sales when applying a promotion, given previous promotion. Note: Normal indicates no promotion is applied and TPR stands for temporary price reduction.

We observe that, in general, applying a combination of feature and display promotion brings about the greatest increase in sales, between 3.35x up to 4.53x increase, regardless of the previous promotion. It is interesting to note, however, that putting products on the same promotion consecutively seems to have a diminishing effect on the sales increase. For example, consecutive display promotion brings about 0.84x increase in sales, whereas applying display promotion without any promotion in the previous week brings about 1.20x increase. This holds true for combination and feature promotion as well. On the other hand, applying a different promotion after another brings a higher boost in sales. A display promotion after a feature promotion increases sales by 2.15x, while a feature promotion after a display promotion increases sales by 3.19x.

From these explorations alone, we have gained valuable insights into the general marketing direction the store chain should take. In terms of pricing strategies, we should note that there is an inflection point in sales effect at a discount rate of 50%. We may want to estimate the trade-offs between further discounting to 50% and the expected increase in sales volume. In terms of in-store advertising, we should avoid having the same promotion with an extended period and switch between the different type of promotions instead.

Analysis & Modelling

Since our MMM approach is a SCAN*PRO model, which performs better using disaggregate store-level data, we will select a store and also a category to model. In our case, we select Cincinnati store in Ohio and specifically, mouthwash products. The reason for selecting Cincinnati store is because it is the largest mainstream store in terms of average weekly sales (see appendix 1) and we specifically select mouthwash products to limit the number of products that we need to feed into the model (see appendix 2). The products that we will model are listed in table 2 below.

Table 2. Selected mouthwash products to be modelled using SCAN*PRO model

Product	UPC	Description	Brand	Size
Product 1	1111035398	PL BL MINT ANTSPTC RINSE	PRIVATE LABEL	1.5L
Product 2	3700031613	SCOPE ORIG MINT MOUTHWASH	P & G	1L
Product 3	3700044982	CREST PH CLN MINT RINSE	P & G	1L
Product 4	31254742735	LSTRNE CL MINT ANTSPTC MW	WARNER	1L
Product 5	31254742835	LSTRNE FRS BRST ANTSPTC MW	WARNER	1L

Although the original SCAN*PRO model compares elasticity across brands, we will instead treat each individual product as its own “brand” in order to compare the product price elasticity. By doing so, we will also be able to not only observe own price elasticity and cross price elasticity across brands, but also measure the potential cannibalisation within each brand based on the elasticity.

Another thing to consider is how the marketing strategy of Cincinnati store affects the neighbouring stores from the same chain, which again lead to cannibalisation of sales. In our case, however, we determined that no stores within its vicinity would be adversely affected by Cincinnati’s marketing strategy due to two reasons. Firstly, in terms of vicinity, there are only two stores within a 2-mile radius while other stores are a significant distance away (see appendix 3). Secondly, the two stores within the vicinity are “value”-type stores which target different customer segmentations (see appendix 3). Therefore, in our SCAN*PRO model we will only use a single store, i.e. Cincinnati store.

We know that SCAN*PRO model is a multiplicative model, originally expressed as:

$$q_{kjt} = \left[\prod_{r=1}^{n}\left(\frac{p_{krt}}{\overline{p_{kr}}}\right)^{\beta rj} \prod_{l=1}^{3}\gamma_{lrj}^{D_{lkrt}}\right]\left[\prod_{t=1}^{T}\delta_{jt}^{X_t}\right]\left[\prod_{k=1}^{K}\lambda_{kj}^{Z_k}\right]e^{u_{kjt}}$$

In our case, we only have a single store, i.e. $k = 1$, and 5 products, i.e.$r = 5$. the model can then be simplified as follows:

$$q_{jt} = \left[\prod_{r=1}^{5}\mathrm{P}_{rt}^{\beta rj}\prod_{l=1}^{3}\gamma_{lrj}^{D_{lrt}}\right]\left[\prod_{t=1}^{51}\delta_{jt}^{X_t}\right]e^{u_{jt}}$$

Where P_{rt} indicates the price index of the product r at time t, i.e. $\mathrm{P}_{rt} = \frac{p_{rt}}{\overline{p_r}}$.

To run an OLS regression based on the model, we linearise the model using natural log function. However, we found that the prices for product 4 and 5 have close to perfect collinearity at ~0.994, i.e. both prices moves perfectly together (see appendix 3). Hence, we average the two prices in each period, t and consider this price applicable for both product 4 and 5. Finally, we obtain the OLS expression below:

$$\widehat{ln(q_J)} = \sum_{r=1}^{4}\hat{\beta}_{rj}ln(\mathrm{P}_r) + \sum_{r=1}^{5}\sum_{l=1}^{3}\hat{\gamma}'_{lrj}D_{lr} + \sum_{t=1}^{51}\hat{\delta}'_{jt}X_t$$

Note: (i) the price index included is up to $r = 4$, where $r = 4$ is the average price index for product 4 and 5; (ii) week binary indicators are only included up to week 51, i.e. $t = 52$, since linear regression would automatically assume week 52 when all week 1 to 51 indicators are zero.

Running the above regression, we obtained the estimator for natural log of sales (see appendix 4). We can then observe the effects of price changes and marketing promotions as summarised in table 3 below.

Table 3. Price elasticities and promotion elasticities across products

	Dependent variable: log of sales of product r, $\ln(q_r)$				
	Product 1, $r = 1$	Product 2, $r = 2$	Product 3, $r = 3$	Product 4, $r = 4$	Product 5, $r = 5$
Price Index 1, $\ln(P_1)$	-1.752^{**} (0.785)	-1.570^{***} (0.574)	1.076 (0.760)	-1.779^{***} (0.664)	-1.856^{***} (0.634)
Price Index 2, $\ln(P_2)$	-0.184 (0.774)	-1.190^{*} (0.611)	-1.439^{*} (0.768)	-0.451 (0.636)	-0.805 (0.627)
Price Index 3, $\ln(P_3)$	0.035 (0.875)	-0.747 (0.636)	-2.283^{***} (0.857)	-0.658 (0.751)	-0.636 (0.723)
Price Index 4, $\ln(P_4)$	0.126 (0.860)	-0.178 (0.612)	-0.032 (0.816)	-2.954^{***} (0.787)	-2.658^{***} (0.730)
Display Promo, D_{1r}	0.504 (0.841)	0.303 (0.288)	0.336^{*} (0.191)	0.268 (0.232)	0.230 (0.352)
Feature Promo, D_{2r}	-	-0.235 (0.259)	0.285 (0.516)	0.554^{*} (0.326)	0.908^{***} (0.337)
Combination, D_{3r}	-	-	1.346^{**} (0.565)	0.613 (0.385)	0.703^{***} (0.340)

Note: green highlighted cells indicate statistical significance in the regression; estimators for week indicators are not included to avoid visual clutter.

From the model we can derive the following interpretations:

Product 1

Product 1, which is a home brand "PRIVATE LABEL", has a price elasticity of -1.752, meaning that a 1% decrease in the price of product 1 increases the sales by 1.752%. The effects from other variables appear to be statistically insignificant to the sales of product 1. Notably, it is also observed that price cuts on product 1 would lead to an increase in sales of products, 2, 4 and 5 as we can see statistically significant effect in the cross-price elasticities of product 1 on the sales of the three products at -1.570, -1.779 and -1.856 respectively. A negative cross elasticity suggests complementarity in products, but this should not be the case for competing products especially across almost all the product ranges. This may suggest endogeneity in the variable, for example, when the home brand products are discounted whenever the store promotes certain campaigns through media or online channel, which in turn boosts the overall sales volume of other products including product 2, 4 and 5.

Product 2

Product 2 has a price elasticity of -1.190, meaning that a 1% price cut leads to a 1.190% increase in sales of product 2. We do not observe statistically significant effect of display nor feature promotion on product 2. Hence, the store may want to consider allocating its budget and resources to other products' marketing mix strategies rather than advertising product 2.

Product 3

Product 3 has a larger price elasticity as compared to product 2 at -2.283, or a 2.283% sales increase with a 1% price cut. It is interesting to note here that the cross-price elasticity of product 2 is statistically significant, with an elasticity value of -1.439. Since both products come from the same manufacturer, a positive cross elasticity would indicate cannibalism. However, in this case we have negative cross elasticity within the same brand. This could occur when a segment of the consumers perceives product 2 having a lower quality with its decrease in price, but with brand loyalty these consumers opt for the more premium alternative which is product 3. This may also explain the reason why product 2 has a relatively low elasticity of -1.190 as compared to the rest of the products which generally have double the elasticity of product 2.

Additionally, we see statistical significance in display only and combination promotion, with elasticity of 0.336 and 1.346 respectively. This means that when product 3 is promoted on the in-store display, the sales increased by 33.6% on average. Similarly, using a combination of feature and display promotion increases the sales of product 3 by 134.6% on average.

Product 4 & 5

For product 4 and 5, we averaged out the price index as P_4 due to collinearity. Product 4 has a price elasticity of -2.954 and product 5 an elasticity of -2.658, which means a 1% price cut leads to 2.954% and 2.658% increase in sales of product 4 and 5 respectively. Featuring both products in the in-store circulars boosts the sales by 55.4% and 90.8% for product 4 and 5 respectively. However, the effect of combining display and feature promotion is only statistically significant on product 5, increasing the sales by 70.3% on average.

Summary

We summarise our findings in table 4 below. Using these insights, the store marketer can properly strategise and select the most optimal marketing strategies for each mouthwash products. For instance, marketing budget should not be allocated towards any form of in-store promotions for product 1 and 2 as they would bring no significant effect on sales. Also, the focus for product 4 and 5 should be on feature promotions while product 3 should get both display and feature exposures where possible.

Table 4. Summary of pricing and promotion strategies on each product of Cincinnati store

Product	Pricing strategies	In-store promotions
Product 1 *Private Label*	• Sales increase by 1.752% every 1% price cut	• No effect on sales
Product 2 *P & G*	• Sales increase by 1.190% every 1% price cut	• No effect on sales
Product 3 *P & G*	• Sales increase by 2.283% every 1% price cut • Sales increase by 1.439% when product 2 price drop by 1%	• Display promotion increases sales by 33.6% • Combining both display and feature promotion increases sales by 134.6%
Product 4 *WARNER*	• Sales increase by 2.954% every 1% price cut	• Feature promotion increases sales by 55.4%
Product 5 *WARNER*	• Sales increase by 2.954% every 1% price cut	• Feature promotion increases sales by 90.8% • Combining both display and feature promotion increases sales by 70.3%

Limitations & Improvements

One potential limitation in the SCAN*PRO approach is that it assumes exogeneity in price elasticity estimates. As we have seen on the cross elasticity of product 1 on other product sales, there may be endogeneity embedded in the variable. To address this issue, we may want to introduce exogenous shock using instrumental variables (IV) to get an unbiased estimate of the prices.

Another limitation is that the existing SCAN*PRO model does not take into consideration the dynamic factors such as leading and lagging prices. The idea behind this dynamic approach is that consumers tend to refer to past prices or potential future prices advertised before they make purchases. This approach however, requires the dataset to have no missing values, which does not apply in our case as our dataset has about ~3.5% missing values (see appendix 5). On this note, we have attempted the dynamic SCAN*PRO model with imputed median prices and observed that lagging and leading prices do show statistically significant effect on sales, especially on product 4 and 5 (see appendix 6).

Nevertheless, the SCAN*PRO model can be extended to other categories and other stores following the same steps to obtain insights into pricing and promotion strategies of other products and stores. There are also other potential marketing analyses that can be performed such as omni-channel dynamics using Vector Auto-Regression (VAR) and sales prediction using Neural Network. However, further enhancement on the dataset would be needed such as including whether any media advertisements or direct marketing has been done.

Conclusion

In conclusion, we have shown that marketing mix modelling (MMM) techniques such as SCAN*PRO model allows us to evaluate the impact of display promotion, feature advertising, and temporary price cuts on the sales of products.

We applied SCAN*PRO model on a single store and a single category, in particular on mouthwash products. We found that not all promotions have a significant impact on product sales and a targeted approach should be taken for each product. Additionally, price cuts on one product may affect another product's sales positively when psychological effects, such as perceived value and brand loyalty, are at play.

It is also important that prior to modelling we perform a certain level of exploratory analysis, even at aggregate level, to uncover low-hanging insights on pricing and promotional strategies. This provides a high-level understanding of the effects of the marketing strategies. For example, how a 50% discount differs in sales impact compared to a 20% discount, or how applying a different promotion mix affects sales more positively than extending the same promotion.

We also uncovered several limitations along the way, such as endogeneity and the lack of dynamic factors. Nevertheless, SCAN*PRO model is still a valuable tool to provide insights on the impact of different marketing strategies on sales and enable marketers to better strategise their marketing resource allocations.

Appendices

Appendix 1. Store selection for SCAN*PRO modelling

Before stores are selected, we view the profiles of the stores in the dataset. From table I, we can see that a large proportion of stores are classified as “mainstream” stores. It suggests that this type of store would likely represent the general consumer population and preferences. Hence, we look into stores that are “mainstream”-type.

Table I. Store type profiles

Store Type	No. of stores	Avg. visits	Avg. sales	Median Price	Median Spend
Mainstream	43	16.99	19.49	$2.99	$31.90
Upscale	17	20.37	23.15	$3.06	$40.59
Value	19	14.00	15.85	$2.99	$23.30

Next, we view the top mainstream stores based on the average total sales as the main criteria. Hence, we select store ID:25027, Cincinnati store in Ohio.

Table II. Top 5 highest sales among mainstream stores

Store ID	Store Name	City Name	State Code	Avg. Total Sales
25027	Cincinnati	Cincinnati	OH	43,892.92
21237	Lebanon	Lebanon	OH	38,465.13
623	Houston	Houston	TX	36,740.69
25229	Cypress	Cypress	TX	34,977.44
17615	Sugarland	Sugar Land	TX	32,490.86

Appendix 2. Category selection for SCAN*PRO modelling

Amongst the four categories, only “FROZEN PIZZA” and “ORAL HYGIENE” has 12 and 13 unique products respectively. The other two categories have 15 unique products recorded, which would prove to be too many to model. Hence, we narrow down to selecting the first two mentioned, “FROZEN PIZZA” or “ORAL HYGIENE”.

Table III. Unique number of products recorded in each category

Category	No. products
BAG SNACKS	15
COLD CEREAL	15
FROZEN PIZZA	12
ORAL HYGIENE	13

We select “ORAL HYGIENE” products and more specifically large-sized mouthwash products (>1L) to narrow down the products further and ensure that the products are of similar nature.

Table IV. Oral hygiene products available

UPC	Product Description	Manufacturer	Size
1111035398	PL BL MINT ANTSPTC RINSE	PRIVATE LABEL	1.5 LT
1111038078	PL BL MINT ANTSPTC RINSE	PRIVATE LABEL	500 ML
1111038080	PL ANTSPTC SPG MNT MTHWS	PRIVATE LABEL	500 ML
3500068914	COLG SPEARMINT WISP	COLGATE	16 CT
3700019521	CREST PH WHTG CLN MINT TP	P & G	4.2 OZ
3700031613	SCOPE ORIG MINT MOUTHWASH	P & G	1 LT
3700044982	CREST PH CLN MINT RINSE	P & G	1 LT
4116709428	ACT MINT A/CAV FLUOR RNS	CHATTEM	532 ML
4116709448	ACT KIDS BBLGUM FLUOR RNS	CHATTEM	532 ML
4116709565	ACT RSTR CL SPLSH MINT MW	CHATTEM	532 ML
31254742725	LSTRNE CL MINT ANTSPTC MW	WARNER	500 ML
31254742735	LSTRNE CL MINT ANTSPTC MW	WARNER	1 LT
31254742835	LSTRNE FRS BRST ANTSPC MW	WARNER	1 LT

<u>Appendix 3. Perfect collinearity between product 4 and 5</u>

We first visualise if there are any correlation between variables in figure I below.

Figure I. Heatmap plot of correlation between independent variables

When calculated we found that the correlation between product 4 and 5 is 0.994, and observed that the price movements are identical as seen in figure II below.

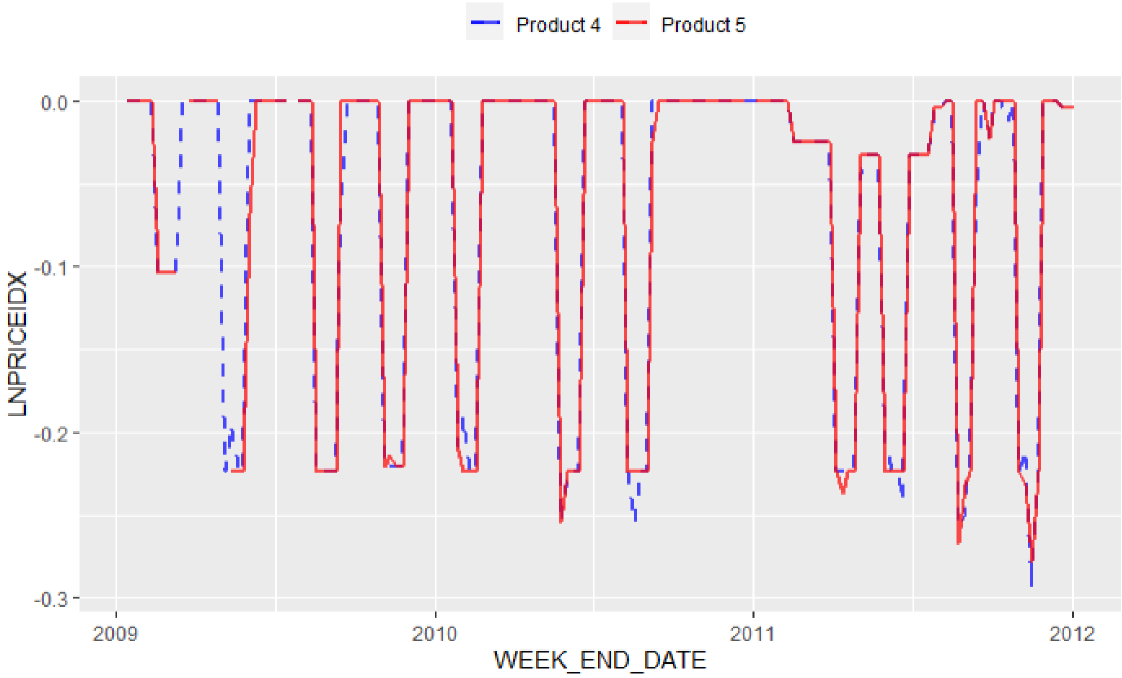

Figure II. Heatmap plot of correlation between independent variables

Appendix 4. Reasons for restricting the model to a single store model

We query the geolocations of the stores by connecting to OpenStreetmap API and search the address based on the store name, city and state. We then plot the store location on the map as shown in figure III below, and calculate the haversine distance between stores.

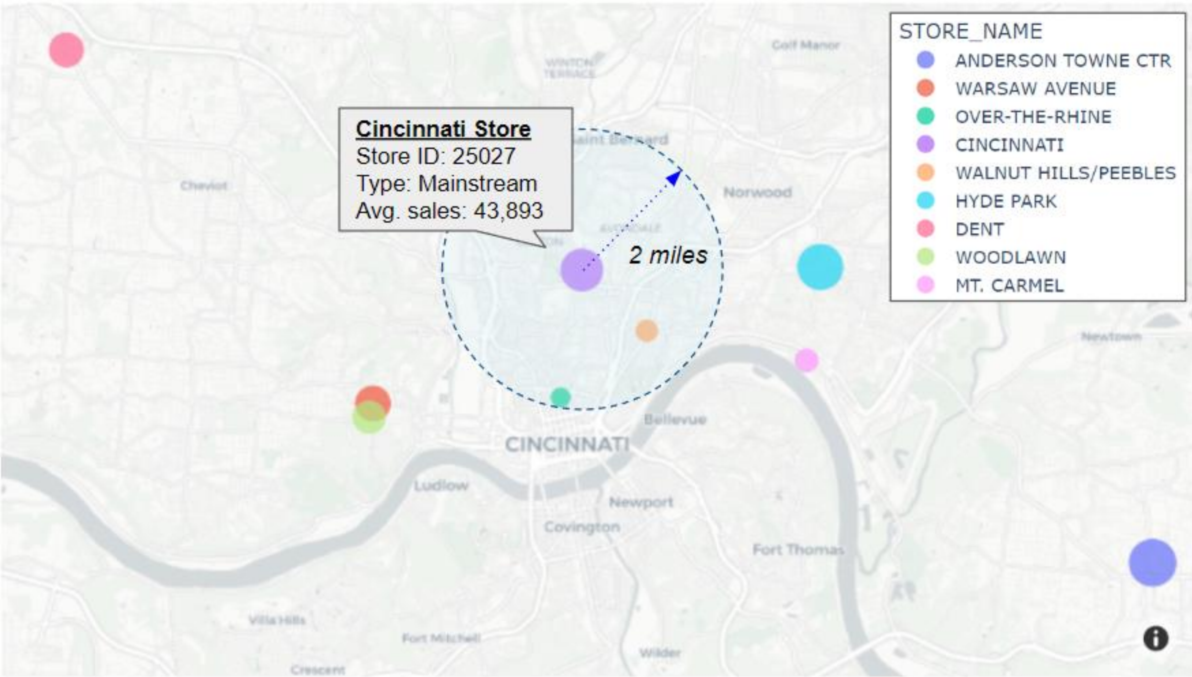

Figure III. Mapbox plot of store locations in Cincinnati, Ohio

Table V. Stores located in Cincinnati, Ohio and the distance to Cincinnati store

Store ID	Store Name	Store Type	Avg. sales	Distance
23055	Walnut Hills	Value	12,999.72	2.12 km
8035	Over-the-Rhine	Value	10,434.71	3.09 km
24991	Hyde Park	Upscale	50,618.99	5.70 km
21213	Mt. Carmel	Mainstream	14,511.79	5.79 km
4259	Warsaw Ave.	Value	31,177.33	5.94 km
15547	Woodlawn	Mainstream	27,357.57	6.19 km
9825	Dent	Mainstream	29,915.90	13.41 km
2277	Anderson T.C.	Upscale	54,052.52	15.35 km

Based on figure III and table V, we can observe that there are only two small stores within the vicinity of the Cincinnati store. Furthermore, these two stores are of different types, indicating a different target consumer segment.

Appendix 5. Missing values in Cincinnati store data

We observe that there are missing values in the sales, price and promotion columns in our selected data as visualised in figure IV below. This is likely due to either an issue with the scanner data or a stock out of the product inventory. As a result, the selected data is not able to be converted into a good time series data, as time series requires values at constant time interval.

Figure IV. Missing values in the selected dataset across selected products

Appendix 6. Dynamic SCAN*PRO model using lag-4 and lead-4

We consider the dynamic approach to SCAN*PRO model to integrate time series effects on sales. To do so, we incorporated up to 4-week lag and lead prices of the product. Missing values in the price variables are imputed with the median price, while promotional variables are imputed with 0, i.e. no promotion. We obtain the regression estimator for promotion, price and leading and lagging prices as shown in table VI.

Table VI. Dynamic SCAN*PRO regression estimators for prices and promotions

	Dependent variable: log of sales of product r, $\ln(q_r)$				
	Product 1, $r=1$	**Product 2, $r=2$**	**Product 3, $r=3$**	**Product 4, $r=4$**	**Product 5, $r=5$**
Price Index 1, $\ln(P_1)$	1.483 (3.972)	1.044 (1.500)	4.155** (2.035)	-0.274 (1.478)	-0.029 (1.674)
Price Index 2, $\ln(P_2)$	-1.232 (0.913)	-1.514 (1.309)	-1.420 (1.021)	-0.687 (0.775)	0.532 (0.858)
Price Index 3, $\ln(P_3)$	-0.322 (0.870)	-0.337 (0.801)	-3.314* (1.740)	-0.657 (0.733)	-1.266 (0.818)
Price Index 4, $\ln(P_4)$	-0.289 (0.942)	-2.124** (0.919)	-0.846 (0.934)	-1.328 (1.373)	-2.396 (1.483)
Lag-1 Index, $\ln(\mathrm{P}_r^{t-1})$	-2.103 (3.341)	-0.366 (1.315)	1.626 (1.628)	0.508 (1.162)	0.589 (1.417)
Lag-2 Index, $\ln(\mathrm{P}_r^{t-2})$	0.367 (2.133)	0.634 (1.312)	0.434 (1.590)	-0.402 (1.147)	-1.207 (1.273)
Lag-3 Index, $\ln(\mathrm{P}_r^{t-3})$	0.181 (3.672)	-0.847 (1.340)	-0.082 (1.658)	-0.917 (1.152)	-0.472 (1.321)
Lag-4 Index, $\ln(\mathrm{P}_r^{t-4})$	0.507 (3.479)	-0.292 (1.119)	0.568 (1.379)	2.384** (1.055)	0.708 (1.144)
Lead-1 Index, $\ln(\mathrm{P}_r^{t+1})$	6.928* (3.922)	-0.103 (1.301)	-0.652 (1.745)	-1.047 (1.204)	0.329 (1.358)
Lead-2 Index, $\ln(\mathrm{P}_r^{t+2})$	-3.670 (3.415)	1.193 (1.215)	1.620 (1.758)	-0.426 (1.225)	-2.455* (1.360)
Lead-3 Index, $\ln(\mathrm{P}_r^{t+3})$	-0.401 (3.228)	-1.043 (1.147)	0.815 (1.820)	2.342* (1.271)	2.549* (1.403)
Lead-4 Index, $\ln(\mathrm{P}_r^{t+4})$	-0.154 (2.649)	-0.514 (1.003)	-1.805 (1.410)	-2.276** (1.036)	-1.881 (1.185)
Display Promo, D_{1r}	0.463 (0.903)	0.823** (0.375)	0.195 (0.244)	0.478* (0.243)	0.190 (0.394)
Feature Promo, D_{2r}	-	-0.001 (0.327)	0.145 (0.577)	1.101*** (0.362)	1.470*** (0.445)
Combination, D_{3r}	-	-	1.096 (0.719)	0.982** (0.434)	0.643 (0.389)

Note: estimators for week indicators are not included to avoid visual clutter.

From table VI, we observe the following:

- Product 1 is only significantly affected by the 1-week leading price, with elasticity of 6.928, which means that when future price is dropped by 1%, the sales of product 1 will decrease by 6.928%; Here we see the delayed purchase effect taking place as consumers anticipate a lower price in the next period.
- Product 2 is now statistically significantly affected by the price of product 4 and 5, with cross elasticity of -2.124 which likely suggest a change in consumer preference towards product 2 from product 4 and 5; Display promotion has an 82.3% boosting effect on sales.
- Product 3 has its own price elasticity of -3.314 which means a 3.314% increase in sales every 1% price reduction; Cross-elasticity with product 1, at 4.155, is observed to be significant which suggests substitution effect taking place between product 3 and 1.
- Product 4 shows responsiveness to all types of in-store promotions but the most effective promotion being feature promotion, with display being 47.8% sales increase, feature being 110.1% and combination being 98.2%; Leading and lagging prices seem to be a statistically significant factor to current sales of the product.
- Product 5 is also responsive to feature promotion, increasing sales by 147.0% when feature advertising is in place; For product 5, only leading prices appear to be a statistically significant factor to the current sales of the product.

The regression model, however, may be inaccurate due to missing data and other endogeneity problems.

References

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