



BUMK 742: Advanced Marketing Analytics

Project #3: Evaluating Sales Promotion Effects Using Scanner Panel Data

Group #1

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Honor Pledge:

We pledge on our honor that we have not given or received any unauthorized assistance on this assignment.

Executive Summary

We were assigned to help Information Resources Inc. to determine which promotion method would result in the greatest increase in sales by analyzing scanner data. To do so we utilized a multilinear regression through SAS and excel and applications such as solver. We sorted through a number of different options of promotions for the four top-selling laundry detergent brands that were being analyzed to determine the best individual promotion technique along with the best combination of promotion techniques for all brands. We found that brand 2 (All) achieves the most increase in total sales when using display ads and feature ads as a promotional technique along with a price cut of brand 2.

Introduction and Background

Information Resources, Inc. (IRI) has provided us with previously collected data on their four top-selling laundry detergents. The stores have tried several promotion methods within 135 weeks to increase its sales volume of the laundry detergent. The data collected consists of the observations of 178 households and their behaviors during the time period from the top four selling laundry detergent brands, including Wisk, All, Tide, and Cheer. In order to identify which methods of promotion are the most effective individually and in overall, we analyze the sales promotion effectiveness of individual consumers patterns when purchasing liquid laundry detergents using household scanners and derived the following results.

Data and Methodology

The data was collected using scanner panel data on laundry detergent purchases made from four stores over 135 weeks. The scanner captured consumer data on if a detergent purchase was made and in what week, the quantity of the detergent purchased, which brand was purchased, whether there was a price cut, and if there were any promotions happening at the time of purchase. There were three different promotion methods that we assessed the effectiveness of price cuts, display advertisements, and feature advertisements. The information of the top four brands is recorded as: 1=Wisk; 2=All; 3=Tide; 4=Cheer. We used the following three models in SAS to evaluate the impact of promotions on different objects.

Firstly, we used a Purchase Incidence Model to assess the influence of promotions on category purchase decisions. The dependent variable, category purchase decision, is a dummy variable, thus we use a binary logit model involving independent variables average regular price (avg_rp), average price cut (avg_pc), whether or not being displayed (cat_disp), whether or not being on feature ads (cat_feat), and whether or not past purchase is on promotion (lbprom). Then, we adopted Brand Choice Model, which is a multinomial logit model, to evaluate customers' brand choices among the four brands mentioned. The following independent variables are included: regular price (regpr), price cut (pcut), whether on display (disp), whether on feature ads (feat). Brand 4 (Cheers) is used as a reference to measure the probability changes of other 3 brands. Finally, we used a semi-log model to estimate the purchase amount of each brand. We take the log of the purchase quantities of each brand as dependent variables and run regression on it with the variables average previous purchase quantity (avol), regular price (regpr), price cut (pcut), and whether or not the past purchase was during a promotion (lbprom). In this third model, only the previous quantity variable was found to be significant, so little can actually be drawn from the results of the models for each brand. However, for this memo we will continue as if all of the results are significant.

Key Findings

During our analysis, we studied the answers to four questions in order to analyze the sales promotion effects using household scanner panel data and to assess the profitability of sales promotions based on the model estimation results. First, we analyzed the effectiveness of three types of sales promotions in influencing customers' purchase incidence, brand-choice, and purchase quantity decision. When looking at the brand purchase quantity the only significant variable was the previous quantity. Additionally, we tested previous quantity; if consumers had a past purchase on promotion, the odds of purchasing detergents decreased by 40.78%. Next, we looked at brand choice. We used the model that tested if they choose each brand and when a brand is chosen. The results demonstrated that a price cut significantly increased odds for one specific brand (consumers chances of picking another brand compared with picking Brand 4 (Cheer)) by 103.76%, a display ad increased odds of brand by 269.64%, and a feature ad increased odds of brand by 47.79%. For purchase incidence, looking at the average regular price of the category as a whole across all brands, average price cut across all brands, if any of the brands had a display or a feature ad, and if the previous purchases by that customer were made during a promotion. We found when there is a price cut of \$1 on average the odds of category purchasing will be increased by 190.35%, if there is a display ads on any brand, the odds of purchasing any brand increase by 63.17%, and if there is a feature ad on any of the brand, the odds will increase by 74.49%. A feature ad motivates customers to purchase any detergent, but a display ad motivates them to pick the specific brand being promoted.

Next, we determined which one of the 3 types of promotions, when offered alone, appears to generate the greatest expected sale quantity increase for Brand 1 (Wisk). By comparing the effects between one of the promotions (price cut, display, and feature) to the sales without any promotions, we drew the following conclusions. When offering a price cut promotion at 0.7, the expected sale quantity increased by 80% with no other promotion. If the detergent is on display, the sales volume has a 314.8% increase compared to the result without any other promotion. With feature ads, there will be a 135.2% upsurge in sales. Consequently, we can conclude that being on display is the most effective way of promotion among these 3.

We then evaluated the effects of combining multiple sales promotion vehicles for a given brand, and settle on which combination is most effective in stimulating sales. The main focus was on Wisk (Brand1) in the results that were found. To begin we estimated four probabilities: price cut and being on display, price cut and feature ads, being on display and feature ads, and all three together. The benchmark is the sales volume of detergent without any promotion. On display products with a price cut of 0.7 dollars per ounce have a sales volume increase of 548.2%. When combining the promotion methods of price cut and features, the total sales volume will increase by 307.6% compared to the baseline. Considering the combination of display option and feature option, the total sales volume will increase by 767.8% compared to the baseline. When combining the price cut of 0.7, display ads and feature ads promotion options, it estimates that the total sales volume will increase by 1185.0%, amounting to 900.979 ounces compared to the baseline. Through measuring the effects on expected sales quantity, we can confirm that the methods from the least to the most powerful dimension are the sequences: price cut < feature ads < price cut & feature ads < display < price cut & display < display & feature ads < price cut & display & feature ads. To conclude, the most effective way of promotion is to use all the methods. If we are adopting two methods, a

combination of being on display and feature ads is the best choice. It is worth paying attention that more methods involved do not guarantee a better outcome because using price cuts and feature ads simultaneously is not as effective as being on display alone from the results above.

Finally, we explored the impact of promoting two (or more) brands simultaneously on category purchase incidence probability, brand choice probabilities, brand-specific sales quantities, and the total category sales quantities. After weighing several options, it can be concluded that Brand 2 has the greatest sales increase of 282.24% with very promotion focusing on Brand 2; price cut, display ads, and feature ads. Besides, when it comes to the price cut for all brands, feature ad and display ad only for Brand 2 leads to the highest upsurge of 554.05%. However if there is no price cut, then, display ad and feature ad promotions exclusively for Brand 3 leads to a greater sales increase of 180.31%.

Conclusion and Recommendations

We recommend that all promotions should be focused on the All brand (brand 2). The promotion of display ads and feature ads for brand 2 exclusively generates the largest increase in total sales compared to other advertising promotion combinations when paired with a price cut of brand 2 (see model 7). However, if you want to avoid making any price cuts altogether, then the optimal combination would be a display and feature for brand 3 exclusively. We are limited in the recommendations we can make regarding this because we are not aware of how much the price cuts affect profit margins. The largest possible increase in sales quantity then you would cut the price on all four brands and exclusively do displays and features on brand 2. The single greatest increase in sales would come from having price cuts on all brands and display and feature ads for brand 2. However, in practical terms excessive price cuts likely want to be avoided to maintain a profit and avoid consumers permanently adapting to these lower prices, hurting sales in the long-term. Thus we recommend using display and feature promotions for brand 2 while also only cutting the price for brand 2.

Some of the limitations that we encountered were centered around the number of brands, how brands interact together, and the impact of price cuts. If we had more than four brands included in the data, the results could have differed. While we know these four brands are the top sellers, they might only make up a small percentage of the total laundry detergent market depending on how many brands there are. Additionally, we found that if brand 2 and brand 3 both have display ads there is the largest increase in sales. If there was a focus on how the brands interact there would be more possibilities for increased sales. When a price cut is utilized it causes an increase in sales from a model standpoint meaning the more price cuts the better sales. However, the conclusions we can draw are limited as there is minimal information about the profit margins and how much extra quantity they would have to sell to make a reasonable profit. In the future, these limitations can be taken into account to increase not only the sales but understand how a greater number of brands interact together and how they can possibly use each other to maximize sales. Moreover, understanding how profits are affected would also be beneficial in making the best possible recommendation to IRI.

Appendices

Figure 1: Model 1: Analysis of Maximum Likelihood Parameter Estimates For Category Purchase Incidence

Analysis Of Maximum Likelihood Parameter Estimates							
Parameter	DF	Estimate	Standard Error	Wald 95% Confidence Limits		Wald Chi-Square	Pr > ChiSq
Intercept	1	1.2006	0.9234	-0.6093	3.0105	1.69	0.1936
avg_rp	1	-0.7629	0.1444	-1.0459	-0.4798	27.90	<.0001
avg_pc	1	1.0659	0.3720	0.3367	1.7951	8.21	0.0042
cat_disp	1	0.4896	0.1401	0.2150	0.7642	12.21	0.0005
cat_feat	1	0.5567	0.1051	0.3507	0.7627	28.04	<.0001
lbpromot	1	-0.5240	0.0841	-0.6889	-0.3591	38.80	<.0001
Scale	0	1.0000	0.0000	1.0000	1.0000		

Model equation:

Binary Logit Model for Category Purchase Incidence=1 →

$$\ln\left(\frac{p_i}{1-p_i}\right) = 1.20 - .76 * avg_{rp} + 1.07 * avg_{pc} + .49 * cat_{disp} + .56 * cat_{feat} - .52 * lb_{promot}$$

Figure 2: Model 2: Analysis of Maximum Likelihood Estimates For Brand Choice

Analysis of Maximum Likelihood Estimates						
Parameter	DF	Parameter Estimate	Standard Error	Chi-Square	Pr > ChiSq	Hazard Ratio
intcpt1	1	-0.43509	0.22097	3.8769	0.0490	0.647
intcpt2	1	0.01602	0.51238	0.0010	0.9751	1.016
intcpt3	1	0.44451	0.21794	4.1600	0.0414	1.560
regpr	1	0.06285	0.25312	0.0616	0.8039	1.065
pcut	1	0.71178	0.23680	9.0347	0.0026	2.038
disp	1	1.30738	0.12124	116.2794	<.0001	3.696
feat	1	0.39064	0.11213	12.1368	0.0005	1.478

Model Equation:

Multinomial Logit Model for Brand Choice →

$$\ln(E[U_k]) = -.44(intcpt1) + .02(intcpt) + .44(intcpt3) + .06 * regpr + .71 * pcut + 1.31 * disp + .39 * feat$$

The intercept of brand choice model could be seen as brand equity - when the intercept becomes larger, people are more likely to choose this brand compared with baseline, Cheer. According to Figure 2, under no promotion activities, the probability of consumers choosing Brand 3(Tide) is about 56% higher than choosing Brand 4 (Cheer). And for Brand 1 (Wisk) having less brand equity than Brand 4 (Cheer), the probability of choosing Wisk is about 35% less than choosing Cheer's. Since the intercept of Brand 2 (All) is not significant, we can assume Brand 2 (All) and Brand 4 (Cheer) has roughly the same brand equity.

Figure 3: Model 3: Semi-log (conditional) Purchase Quantity Model For Brand 1 Purchase Quantity

Parameter Estimates					
Variable	DF	Parameter Estimate	Standard Error	t Value	Pr > t
Intercept	1	3.54580	0.47817	7.42	<.0001
avol	1	0.00689	0.00091620	7.52	<.0001
regpr1	1	0.03648	0.06617	0.55	0.5823
pcut1	1	0.00891	0.08451	0.11	0.9162
lbpromot	1	0.07215	0.05597	1.29	0.1993

Model Equation:

Semi-log Purchase Quantity Model for Brand 1→

$$\ln(E[S_i, k, t]) = 3.55 + .007 * avol + .04 * regpr1 + .01 * pcut1 + .07 * lbpromot$$

Figure 4: Model 4:Semi-log (conditional) Purchase Quantity Model For Brand 2 Purchase Quantity

Parameter Estimates					
Variable	DF	Parameter Estimate	Standard Error	t Value	Pr > t
Intercept	1	4.29652	0.36209	11.87	<.0001
avol	1	0.00671	0.00065663	10.22	<.0001
regpr2	1	-0.10162	0.07488	-1.36	0.1765
pcut2	1	0.25655	0.15216	1.69	0.0937
lbpromot	1	0.09022	0.05573	1.62	0.1073

Model Equation:

Semi-log Purchase Quantity Model for Brand 2→

$$\ln(E[S_i, k, t]) = 4.30 + .01 * avol - .10 * regpr2 + .26 * pcut2 + .09 * lbpromot$$

Figure 5: Model5: Semi-log (conditional) Purchase Quantity Model For Brand 3 Purchase Quantity

Parameter Estimates					
Variable	DF	Parameter Estimate	Standard Error	t Value	Pr > t
Intercept	1	3.69781	0.33773	10.95	<.0001
avol	1	0.00669	0.00056032	11.94	<.0001
regpr3	1	0.02871	0.04396	0.65	0.5142
pcut3	1	0.01672	0.05946	0.28	0.7788
lbpromot	1	0.01880	0.03657	0.51	0.6076

Model Equation:

Semi-log Purchase Quantity Model for Brand 3→

$$\ln(E[S_i, k, t]) = 3.70 + .01 * avol + .03 * regpr3 + .02 * pcut3 + .02 * lbpromot$$

Figure 6: Model 6: Semi-log (conditional) Purchase Quantity Model For Brand 4 Purchase Quantity

Parameter Estimates					
Variable	DF	Parameter Estimate	Standard Error	t Value	Pr > t
Intercept	1	3.87265	0.30464	12.71	<.0001
avol	1	0.00297	0.00057447	5.16	<.0001
regpr4	1	0.06738	0.04757	1.42	0.1594
pcut4	1	0.05457	0.04516	1.21	0.2294
lbpromot	1	0.00227	0.03024	0.08	0.9403

Model Equation:

Semi-log Purchase Quantity Model for Brand 4→

$$\ln(E[S_i, k, t]) = 3.87 + .003 * avol + .07 * regpr4 + .05 * pcut4 + .002 * lbpromot$$

Figure 7: Model 7: Solver Optimization for display and feature ads

Solver Parameters

Set Objective:

To: ☒ Max ☐ Min ☐ Value Of:

By Changing Variable Cells:

Subject to the Constraints:

\$D\$13 = binary

\$D\$14 = binary

\$D\$15 = binary

\$D\$16 = binary

\$D\$17 = binary

\$D\$18 = binary

\$D\$19 = binary

\$D\$20 = binary

☒ Make Unconstrained Variables Non-Negative

Select a Solving Method:

Solving Method

Select the GRG Nonlinear engine for Solver Problems that are smooth nonlinear. Select the LP Simplex engine for linear Solver Problems, and select the Evolutionary engine for Solver problems that are non-smooth.

Figure 8: Descriptive Statistics of means

Variable	N	Mean	Std Dev	Minimum	Maximum
regpr1	19157	7.1818259	0.3085522	6.7470000	7.7690000
regpr2	19157	4.5918611	0.3323986	4.1200000	5.0280000
regpr3	19157	7.2852565	0.3518476	6.8520000	7.8030000
regpr4	19157	6.5377189	0.2910547	5.7100000	6.7900000
pcut1	19157	0.1553111	0.2605256	0	1.2170000
pcut2	19157	0.0576519	0.1151700	0	0.5420000
pcut3	19157	0.0360955	0.1396495	0	1.2050000
pcut4	19157	0.0228914	0.1249738	0	1.0220000
disp1	19157	0.4170277	0.4930804	0	1.0000000
disp2	19157	0.3398758	0.4736792	0	1.0000000
disp3	19157	0.2928955	0.4551028	0	1.0000000
disp4	19157	0.0887404	0.2843761	0	1.0000000
feat1	19157	0.2391293	0.4265630	0	1.0000000
feat2	19157	0.2221120	0.4156769	0	1.0000000
feat3	19157	0.2321345	0.4222054	0	1.0000000
feat4	19157	0.0588819	0.2354096	0	1.0000000
avg_rp	19157	6.3991656	0.2767827	5.9780000	6.8475000
avg_pc	19157	0.0679875	0.0894214	0	0.4497500
cat_disp	19157	0.8157854	0.3876693	0	1.0000000
cat_feat	19157	0.6718693	0.4695449	0	1.0000000

In this chart, we find the regular price of Brand 2(All) is about 4.59, which is the least among all the brands, and the regular price of Brand 3(Tide) is about 7.29, which is the largest among all the brands. There is also some information about promotions concluded in this chart. For the price cut, Brand 1(Wisk) has the largest price cut of about 0.15 and Brand 4(Cheer) has the least of 0.02. Besides, when it comes to the display ad and feature ad, Brand 1(Wisk) has the most frequency of both feature ad and display ad promotion and Brand 4(Cheer) has the least in both of that. For the situation whether any brand in the category is on in-store, the average occurring probability is 81.58%. Also, for the situation whether any brand in the category is on feature advertising, the average occurring probability is 67.19%.

Figure 9 : Descriptive Statistics of brand

The MEANS Procedure

Analysis Variable : volume						
choice	N Obs	N	Mean	Std Dev	Minimum	Maximum
0	18376	18376	0	0	0	0
1	164	164	111.2804878	38.8982547	50.0000000	200.0000000
2	172	172	128.7906977	59.2252349	50.0000000	512.0000000
3	324	324	119.1481481	44.5166991	50.0000000	400.0000000
4	121	121	105.6198347	23.5192319	90.0000000	200.0000000

The chart is about the summary statistics of four brands volume. The mean volume sales of Brand 1 (Wisk) is about 111.28. The maximum volume sales is 200 and the minimum volume sales is 50. The standard deviation is 38.90. While the average volume sales of brand 2 (All) is 128.79. The maximum volume sales of 512, which is the largest volume among four brand. and the minimum volume sales is 50. The standard deviation is 59.23. Additionally, the mean volume sales of Brand 3 (Tide) is 119.15. The maximum volume sales and the minimum volume sales is 400 and 50. The standard deviation is 44.52. The last brand Cheer has the smallest average volume sales, but the minimum volume sales is 90. The maximum volume sales is 200. The standard deviation is 23.52.

Figure 10 : Frequency Table of Purchase Incidence

The FREQ Procedure				
Frequency Percent Row Pct Col Pct	Table of choice by incid			
	choice	incid		Total
		0	1	
0	18376	0	18376	
	95.92	0.00	95.92	
	100.00	0.00		
	100.00	0.00		
1	0	164	164	
	0.00	0.86	0.86	
	0.00	100.00		
	0.00	21.00		
2	0	172	172	
	0.00	0.90	0.90	
	0.00	100.00		
	0.00	22.02		
3	0	324	324	
	0.00	1.69	1.69	
	0.00	100.00		
	0.00	41.49		
4	0	121	121	
	0.00	0.63	0.63	
	0.00	100.00		
	0.00	15.49		
Total	18376	781	19157	
	95.92	4.08	100.00	

This table is about customers' purchase incidence among the four brands. There are 19157 choices in total. 18376 of them did not make purchase decisions, which is 95.92% of the total. Among the other 781 purchases, 164, 172, 324 and 121 choices are brand 1, 2, 3, and 4, accounting for 21%, 22.02%, 41.49%, and 15.49% respectively.

Figure 11: Criteria for assessing goodness of fit for Binary Logit Model for Category Purchase Incidence = 1

Criteria For Assessing Goodness Of Fit			
Criterion	DF	Value	Value/DF
Log Likelihood		-3184.7055	
Full Log Likelihood		-3184.7055	
AIC (smaller is better)		6381.4109	
AICC (smaller is better)		6381.4153	
BIC (smaller is better)		6428.5735	

Figure 12: Analysis of Maximum Likelihood Parameter Estimates For Category Purchase Incidence = 1

Analysis Of Maximum Likelihood Parameter Estimates							
Parameter	DF	Estimate	Standard Error	Wald 95% Confidence Limits		Wald Chi-Square	Pr > ChiSq
Intercept	1	1.2006	0.9234	-0.6093	3.0105	1.69	0.1936
avg_rp	1	-0.7629	0.1444	-1.0459	-0.4798	27.90	<.0001
avg_pc	1	1.0659	0.3720	0.3367	1.7951	8.21	0.0042
cat_disp	1	0.4896	0.1401	0.2150	0.7642	12.21	0.0005
cat_feat	1	0.5567	0.1051	0.3507	0.7627	28.04	<.0001
lbpromot	1	-0.5240	0.0841	-0.6889	-0.3591	38.80	<.0001
Scale	0	1.0000	0.0000	1.0000	1.0000		

Figure 13 : Analysis of Maximum Likelihood Estimates for Multinomial Logit Model for Brand Choice

Analysis of Maximum Likelihood Estimates						
Parameter	DF	Parameter Estimate	Standard Error	Chi-Square	Pr > ChiSq	Hazard Ratio
intcpt1	1	-0.43509	0.22097	3.8769	0.0490	0.647
intcpt2	1	0.01602	0.51238	0.0010	0.9751	1.016
intcpt3	1	0.44451	0.21794	4.1600	0.0414	1.560
regpr	1	0.06285	0.25312	0.0616	0.8039	1.065
pcut	1	0.71178	0.23680	9.0347	0.0026	2.038
disp	1	1.30738	0.12124	116.2794	<.0001	3.696
feat	1	0.39064	0.11213	12.1368	0.0005	1.478