SCAN*PRO: Understanding the effectiveness of price, display and promotional activity for competing brands of beer

Retail Marketing Analytics - Individual Report

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Abstract

In this analysis, the SCAN*PRO model is applied to understand the effect of promotional activity on the unit sales of three competing brands of beer sold by a supermarket store. This information was used to make recommendations to the store manager so that they could tailor the promotional activity mix accordingly for each individual brand to increase unit sales. Three separate SCAN*PRO models were created, one for each brand, to estimate the own and cross brand elasticities for price, display and feature promotional activity whilst also incorporating the effect of seasonality on sales. Beer sales for all three brands were highly seasonal with unit sales increased up to 45% in the summer months. Feature promotions were found to be more effective at increasing unit sales than display promotions, however, the result was only statistically significant for one brand of beer. Brand 1 unit sales were increased 9.9% when featured in a given week. Display advertising was most effective for brand 2 with an uplift of 2.5% in unit sales when the percentage of stock keeping units on display was increased by 1%, but was ineffective for the other two brands. Consumers of brand 3 were found to be the most price sensitive with a 6.7% increase in sales for a 1% decrease in price.

Contents

1 Introduction

Retailers are interested in understanding the impact that promotional activity has on product sales. The SCAN*PRO model (Wittink et al. 1988) is a popular method for quantifying the interaction effects between various promotional activities such as price reductions, display promotions and feature promotions, allowing store managers to understand the effectiveness of promotional campaigns for different products (Andrews et al. 2008, Srinivasan et al. 2004).

In this analysis, the SCAN*PRO model was used to understand the effects of promotional activity on the sales of three competing brands of beer for a Chicago based grocery store, Dominick's. The insights gained from the model were used to make recommendations to the store manager on how to tailor promotional activity for each brand of beer and effectively deploy their promotion resources.

1.1 Business Objective & Research Question

The following business objective and corresponding research questions were evaluated in the analysis:

Business Objective: What is the most effective form of promotion to boost unit sales of each beer brand?

- Which types of promotion are more effective for each beer brand: price reduction, display or feature promotion?
- Are promotions equally effective for each brand of beer?
- How does promotional activity for each brand interact with sales of other beer brands?

1.2 Assumptions

The main assumptions of the analysis are as follows:

- There is a finite amount of promotional resource, and therefore there is a benefit to optimising the allocation of promotional activity for each brand.
- The manager has full control over setting the level of feature, display and price promotional activity. For example, there are no contractual obligations with brand suppliers which guarantees a certain level of promotion.

1.3 About SCAN*PRO

SCAN*PRO is a store-level model which is able to quantify the effect of price changes and promotional activities on the unit sales of products for retailers. The model is a multiplicative model which includes own and cross brands elasticities for price, feature and display advertising. The SCAN*PRO model is shown in equation 1 (Leeflang et al. 2002):

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

For $k = 1, ..., K; t = 1, ...T$

Where:

- q_{kjt}: unit sales for brand j in store k in week t
- p_{krt}: unit price for brand r in store k in week t
- D_{1krt}: binary indicator variable for display advertising
- D_{2krt}: binary variable for feature advertising
- X_t: seasonal indicator variable
- Z_k: indicator variable for store k
- e: error term for unobserved or missing variables from the model

The parameters β_{rj}, γ_{lrj}, δ_{jt} and λ_{kj} are to be estimated. These parameters can be estimated using non-linear optimisation techniques, however, this can be computationally expensive, highly sensitive to model inputs and has no guarantee of reaching a global minimum. Therefore, it is advantageous to take the log transformation of equation 1 to make the model additive which can be solved using simple linear estimation techniques such as OLS.

The additive model to be estimated thus becomes:

$$ln(q_{kjt}) = \sum_{r=1}^{n}\beta_{rj}ln\left(\frac{p_{krt}}{\bar{p}_{kr}}\right) + \sum_{r=1}^{n}\sum_{l=1}^{2}ln(\gamma_{lrj})D_{lkrt} + \sum_{t=1}^{T}ln(\delta_{jt})X_t + \sum_{k=1}^{K}ln(\lambda_{kj})Z_k + e_{kjt} \tag{2}$$

The model parameters from equation 2 can then be converted back into the multiplicative form in equation 1 to estimate unit sales for the week.

1.4 Software Used

All analysis was conducted using Python (programming language). Details of code and packages used are included in the supplementary information.

2 Data

2.1 Description

The dataset employed for the analysis consists of scanner records for beer category products from a grocery store, Dominick's Finer Foods store (Dominick's). The original source of the dataset was from Chicago Booth and a description of the dataset is included in Srinivasan et al. (2004). However, the dataset used for this analysis was an adapted dataset shared by the Imperial College Retail Marketing Analytics teaching team via Slack (March 19th - *beer_data_chicago_Dominicks.xlsx*).

The data covers 227 weeks (4 years 5 months) of sales for three brands of beer between 1989 and 1993. The raw data contained the following attributes for each brand:

Table 1: Raw dataset features

Variable Name	Description
`SALESBRAND*`	average sales ($) for brand *
`PRICEBRAND*`	retail price ($) for brand *
`display_brand*`	percentage of SKUs† on display for brand *
`FEATUREBRAND*`	percentage of SKUs featured in the store for brand *
`RETAILERMARGINBRAND*`	average retailer margin (%) for brand *
`WHOLESALEPRICEBRAND*`	average wholesale price ($) for brand *

∗ Brand 1,2 or 3, † Stock keeping units

The display and feature attributes are expressed as the percentage of stock keeping units (SKUs) which were promoted by the store in a given week. The literature (Srinivasan et al. 2004) is not clear what 'display' and 'feature' promotions specifically involved at the store, so it is assumed that for a display promotion the product was displayed prominently and for a feature promotion the product was 'on offer'.

The raw data did not contain a *unit sales* variable which is the desired target variable for the SCAN*PRO model. Therefore, a unit sales variable, *UNITSBRAND**, was created for each brand by dividing the sales of the brand by its average retail price for each week.

The retailer margin is not a factor in the SCAN*PRO model described in equation 1 and was therefore not considered in the model estimation.

The wholesale price is not directly used in the SCAN*PRO model as the retail price is used instead. However, retail prices can be subject to issues with endogeneity as they may be set by the store manager in response to how well the the product is selling, and therefore may not be completely independent of the target variable. The wholesale price can be a useful alternative to retail price as an instrument variable if endogeneity exists and was kept in the dataset for further investigation [1].

[1]Granger causality tests showed that the *PRICEBRAND** variable was not endogenous - see *notebooks/02_alternative_models.ipynb* in the supplementary information

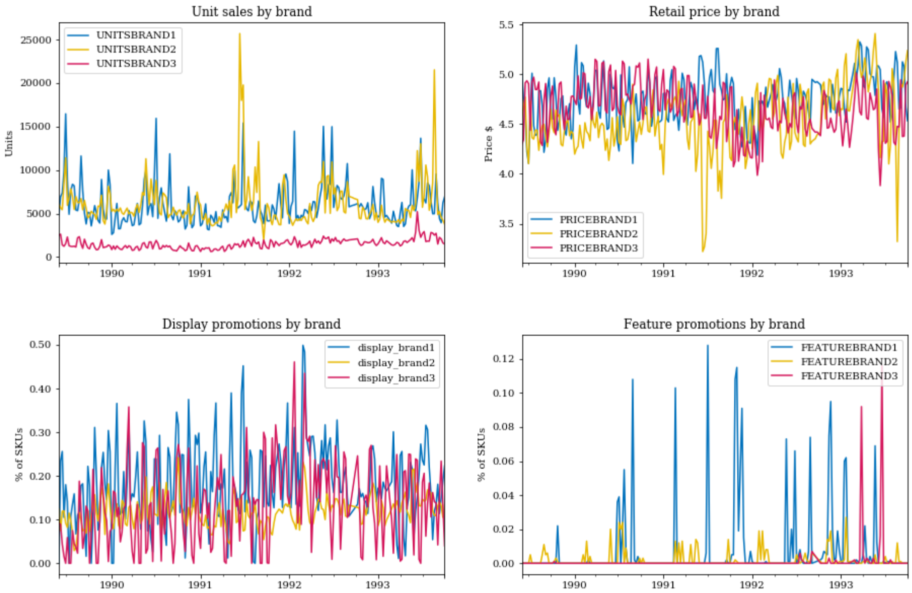

Figure 1: Unit sales, price, display and feature data for each brand

2.2 Assumptions

The data observations are given with weekly interval and it is assumed the display and feature promotions lasted for the entire week.

The start date for the data observations was not explicit in the literature (Srinivasan et al. 2004). It was assumed the data observations started in the first week of June 1989 (4th June 1989) which is consistent with the seasonality exhibited in figure 2.

2.3 Exploratory Analysis

The unit sales, prices, display and feature variables for each brand are shown in figure 1.

Brands 1 and 2 are the most popular with similar weekly unit sales but also exhibit a greatest variation in unit sales. Whereas brand 3 has a much more consistent but lower sales volume. It appears most of the variation in unit sales is driven by seasonal factors.

The retail price of each brand is similar and hovers between approximately $4 and $5 throughout the time period.

Each brand appears to have a certain percentage of stock keeping units 'on display' in almost every week. There is a very high variation in the percentage of SKUs from week to week ranging from 0% to 50%, with brand 1 having the highest average percentage of SKUs on display each week (14%).

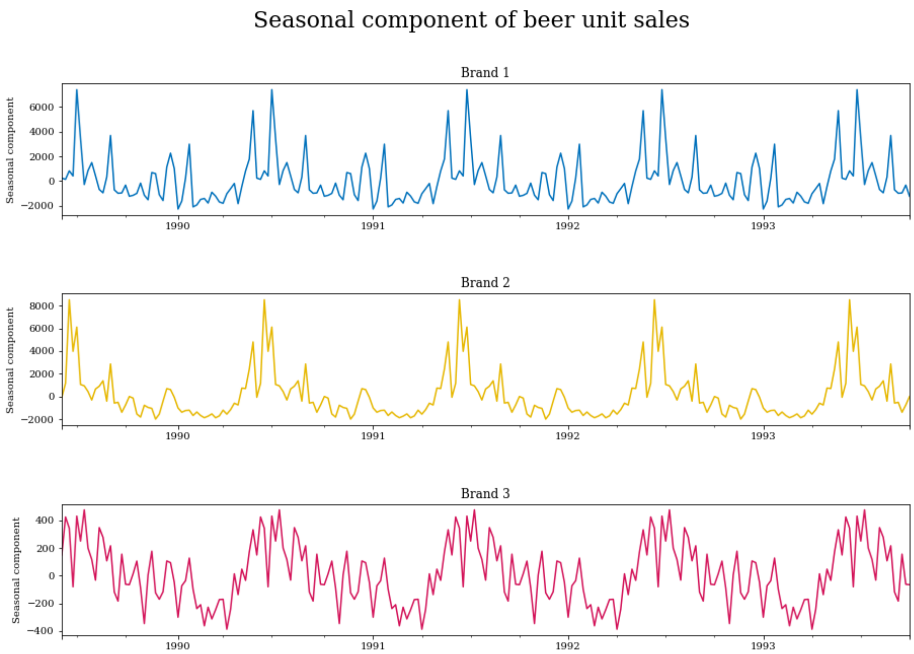

Figure 2: Seasonal component of unit sales for each brand unit sales

The 'feature' promotional activity was used more sparingly than the 'display' promotions. Most weeks typically have no brands or just one brand featured. Brand 1 was featured the most and tended to have a greater percentage of SKUs featured in the week compared to when other brands were featured. Brand 2 was featured more consistently than the other brands albeit with a smaller percentage of SKUs. Brand 3 was only featured towards the end of the time period of observations.

The SCAN*PRO model also incorporates seasonal effects on the unit sales. Figure 2 shows the seasonal component of the unit sales for each beer brand. There are clear and significant seasonal trends in the data for all brands, with unit sales peaking in the summer months (May-August) as well as smaller peaks across the Christmas holiday period.

3 Model Estimation

3.1 Methodology

3.1.1 Data Preparation

In order for the model to be estimated using linear methodologies (equation 2), the *UNITSBRAND**, *PRICEBRAND** and *display_brand** variables were log transformed. Due to the presence of a small number of zero values in the *display_brand** variables, a $log(x+1)$ transformation (Wooldridge 2016) was used to avoid *-inf* values after the transformation.

The *FEATUREBRAND** variable could not be log transformed in this manner as the majority of values were zero for each brand (figure 1) which would make interpretation of the coefficients less meaningful. Therefore the *FEATUREBRAND** variable was encoded as a new binary variable, *binary_FEATUREBRAND**, which was labelled as 1 if the percentage of SKUs was greater than 0.02 and 0 otherwise. Even though the percentage of SKUs featured was not the same for each brand, the binary variable still preserved important information about the effects of feature promotions on unit sales.

Finally, eleven dummy variables $(k-1)$ were created for each month of the year to encode the seasonality observed in figure 2.

3.1.2 Model Estimation & Validation

A separate model was created for each of the three competing brands of beer. The log unit sales (*log_UNITSBRAND**) for each brand were estimated using a regression model with the *log_PRICEBRAND**, *log_display_brand**, *binary_FEATUREBRAND** and seasonal dummy variables as inputs (see *notebooks/01_regression_modelling.ipynb* in the supplementary information). [2]

To validate the models, 80% of the data was randomly sampled for model estimation (training) with 20% reserved for validating the accuracy of the model on unseen data. Once the model had been validated, the model was re-estimated using the full dataset to obtain the final model coefficients which could be used for interpretation.

Table 2 shows the R^2 of the SCAN*PRO model for each brand model trained on 80% of the available data. All three models gave reasonably good R^2 values with the models explaining approximately 80% of the variation in the data. The root mean squared error (RMSE) of the models on the unseen test data was approximately 0.17 for each model (equivalent to an average prediction error of $\pm 2\%$). The R^2 and RMSE for each model are consistent which suggests that the model is generalisable with good performance across all three brands.

[2] Alternative combinations of model inputs were also investigated, however, these were less accurate and not selected for further investigation (see *02_alternative_models.ipynb* in the supplementary information)

Table 2: R^2 for models trained on 80% of data and RMSE of model on unseen test data

Model	R^2	RMSE
Brand 1	0.792233	0.165940
Brand 2	0.812804	0.172020
Brand 3	0.813989	0.177375

3.2 Results

The final model coefficients for each brand, estimated using all available observations, are reported in tables 3, 4 and 5 respectively.

Table 3: Brand 1: SCAN*PRO coefficients

Dep. Variable:	log_UNITSBRAND1	**R-squared:**	0.777
Model:	OLS	**Adj. R-squared:**	0.756
Method:	Least Squares	**F-statistic:**	35.96
Date:	Sat, 11 Apr 2020	**Prob (F-statistic):**	3.77e-56
Time:	16:22:19	**Log-Likelihood:**	94.246
No. Observations:	227	**AIC:**	-146.5
Df Residuals:	206	**BIC:**	-74.57
Df Model:	20		

	coef	**std err**	**t**	**P> |t|**	**[0.025**	**0.975]**
const	18.8007	1.033	18.206	0.000	16.765	20.837
log_PRICEBRAND1	-4.8740	0.369	-13.209	0.000	-5.601	-4.146
log_PRICEBRAND2	0.3262	0.205	1.589	0.114	-0.079	0.731
log_PRICEBRAND3	-1.4018	0.362	-3.873	0.000	-2.115	-0.688
log_display_brand1	0.6736	0.199	3.390	0.001	0.282	1.065
log_display_brand2	0.7605	0.414	1.837	0.068	-0.056	1.577
log_display_brand3	-0.3266	0.215	-1.521	0.130	-0.750	0.097
binary_FEATUREBRAND1	0.0939	0.040	2.376	0.018	0.016	0.172
binary_FEATUREBRAND2	0.0075	0.042	0.179	0.858	-0.075	0.090
binary_FEATUREBRAND3	0.0148	0.107	0.138	0.890	-0.196	0.225
August	0.2292	0.057	4.019	0.000	0.117	0.342
December	-0.0772	0.061	-1.266	0.207	-0.198	0.043
February	-0.1557	0.059	-2.625	0.009	-0.273	-0.039
January	-0.0700	0.060	-1.174	0.242	-0.188	0.048
July	0.2674	0.056	4.737	0.000	0.156	0.379
June	0.3694	0.059	6.304	0.000	0.254	0.485
March	-0.1076	0.060	-1.796	0.074	-0.226	0.011
May	0.3299	0.058	5.658	0.000	0.215	0.445
November	-0.0992	0.061	-1.633	0.104	-0.219	0.021
October	-0.0726	0.058	-1.244	0.215	-0.188	0.042
September	0.0766	0.055	1.383	0.168	-0.033	0.186

Omnibus:	11.282	**Durbin-Watson:**	1.446
Prob(Omnibus):	0.004	**Jarque-Bera (JB):**	11.511
Skew:	0.520	**Prob(JB):**	0.00317
Kurtosis:	3.366	**Cond. No.**	317.

Table 4: Brand 2: SCAN*PRO coefficients

Dep. Variable:	log_UNITSBRAND2	**R-squared:**	0.805
Model:	OLS	**Adj. R-squared:**	0.786
Method:	Least Squares	**F-statistic:**	42.52
Date:	Sat, 11 Apr 2020	**Prob (F-statistic):**	6.01e-62
Time:	16:36:52	**Log-Likelihood:**	111.22
No. Observations:	227	**AIC:**	-180.4
Df Residuals:	206	**BIC:**	-108.5
Df Model:	20		

	coef	**std err**	**t**	**P> |t|**	**[0.025**	**0.975]**
const	16.6887	0.958	17.416	0.000	14.799	18.578
log_PRICEBRAND1	-0.5023	0.342	-1.467	0.144	-1.177	0.173
log_PRICEBRAND2	-3.6822	0.190	-19.329	0.000	-4.058	-3.307
log_PRICEBRAND3	-0.6435	0.336	-1.916	0.057	-1.306	0.019
log_display_brand1	-0.1127	0.184	-0.611	0.542	-0.476	0.251
log_display_brand2	2.5825	0.384	6.724	0.000	1.825	3.340
log_display_brand3	-0.3336	0.199	-1.675	0.095	-0.726	0.059
binary_FEATUREBRAND1	0.0152	0.037	0.414	0.679	-0.057	0.087
binary_FEATUREBRAND2	0.0325	0.039	0.841	0.401	-0.044	0.109
binary_FEATUREBRAND3	0.0320	0.099	0.323	0.747	-0.163	0.227
August	0.1409	0.053	2.662	0.008	0.037	0.245
December	-0.0739	0.057	-1.306	0.193	-0.186	0.038
February	-0.1645	0.055	-2.989	0.003	-0.273	-0.056
January	-0.1237	0.055	-2.235	0.027	-0.233	-0.015
July	0.1566	0.052	2.989	0.003	0.053	0.260
June	0.2464	0.054	4.531	0.000	0.139	0.354
March	-0.0576	0.056	-1.035	0.302	-0.167	0.052
May	0.2229	0.054	4.121	0.000	0.116	0.330
November	-0.0993	0.056	-1.761	0.080	-0.211	0.012
October	-0.1148	0.054	-2.119	0.035	-0.222	-0.008
September	-0.0330	0.051	-0.642	0.522	-0.134	0.068

Omnibus:	8.722	**Durbin-Watson:**	1.414
Prob(Omnibus):	0.013	**Jarque-Bera (JB):**	16.292
Skew:	0.071	**Prob(JB):**	0.000290
Kurtosis:	4.305	**Cond. No.**	317.

Table 5: Brand 3: SCAN*PRO coefficients

Dep. Variable:	log_UNITSBRAND3	**R-squared:**	0.802
Model:	OLS	**Adj. R-squared:**	0.783
Method:	Least Squares	**F-statistic:**	41.69
Date:	Sat, 11 Apr 2020	**Prob (F-statistic):**	2.92e-61
Time:	16:37:01	**Log-Likelihood:**	100.73
No. Observations:	227	**AIC:**	-159.5
Df Residuals:	206	**BIC:**	-87.53
Df Model:	20		

	coef	**std err**	**t**	**P> |t|**	**[0.025**	**0.975]**
const	14.9740	1.004	14.920	0.000	12.995	16.953
log_PRICEBRAND1	0.4840	0.359	1.350	0.179	-0.223	1.191
log_PRICEBRAND2	1.0858	0.200	5.442	0.000	0.692	1.479
log_PRICEBRAND3	-6.1407	0.352	-17.455	0.000	-6.834	-5.447
log_display_brand1	0.1762	0.193	0.912	0.363	-0.205	0.557
log_display_brand2	1.5551	0.402	3.866	0.000	0.762	2.348
log_display_brand3	-0.4286	0.209	-2.055	0.041	-0.840	-0.017
binary_FEATUREBRAND1	0.0125	0.038	0.326	0.745	-0.063	0.088
binary_FEATUREBRAND2	-0.0133	0.040	-0.328	0.743	-0.093	0.067
binary_FEATUREBRAND3	0.1231	0.104	1.186	0.237	-0.082	0.328
August	0.2225	0.055	4.016	0.000	0.113	0.332
December	-0.0903	0.059	-1.522	0.129	-0.207	0.027
February	-0.1031	0.058	-1.789	0.075	-0.217	0.011
January	-0.0728	0.058	-1.256	0.210	-0.187	0.041
July	0.2690	0.055	4.903	0.000	0.161	0.377
June	0.2794	0.057	4.906	0.000	0.167	0.392
March	-0.1100	0.058	-1.888	0.060	-0.225	0.005
May	0.2266	0.057	3.998	0.000	0.115	0.338
November	-0.0538	0.059	-0.911	0.364	-0.170	0.063
October	-0.0464	0.057	-0.818	0.415	-0.158	0.065
September	0.1006	0.054	1.869	0.063	-0.006	0.207

Omnibus:	3.704	**Durbin-Watson:**	1.106
Prob(Omnibus):	0.157	**Jarque-Bera (JB):**	3.343
Skew:	0.244	**Prob(JB):**	0.188
Kurtosis:	3.339	**Cond. No.**	317.

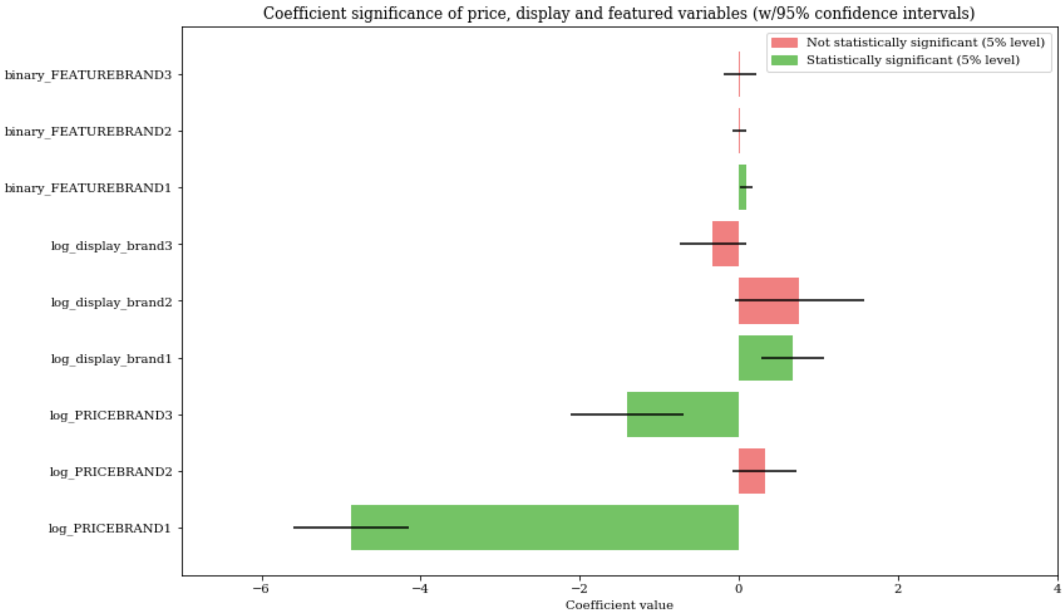

Figure 3: Brand 1 key model coefficients with confidence intervals

4 Discussion

The R^2 values for each model range from 0.77 to 0.80, indicating that the models are a good fit for the data and explain approximately 80% of the variation in log unit sales for each brand.

Seasonality is a significant factor affecting unit sales for all brands. For example, sales in the summer months (May - August) can be increased by up to 45% (brand 1, June $[e^{0.3694} = 1.447]$). The magnitude of seasonal effects is similar for all brands and is the main contributing factor to log unit sales.

While seasonality is an important factor for estimating unit sales, it is out of the store manager's control. The coefficients for price, display and feature variables will provide more valuable insights for the store manager assessing the effectiveness of promotional activity. The coefficients of the *binary_FEATUREBRAND**, *log_display_brand** and *log_PRICEBRAND** variables and their confidence intervals are shown in graphical form in figures 3, 4 and 5.

4.1 Price

The own brand price elasticities of brand 1, 2 and 3 are -4.874, -3.682, -6.141 respectively. Due to the log-log form of the model, these coefficients can be interpreted as meaning that a decrease in price by 1% will increase the unit sales by 4.874%, 3.682% and 6.141% for each brand respectively. This suggests brand 3 customers are most price sensitive. The confidence intervals for the own brand price elasticities are small compared to the

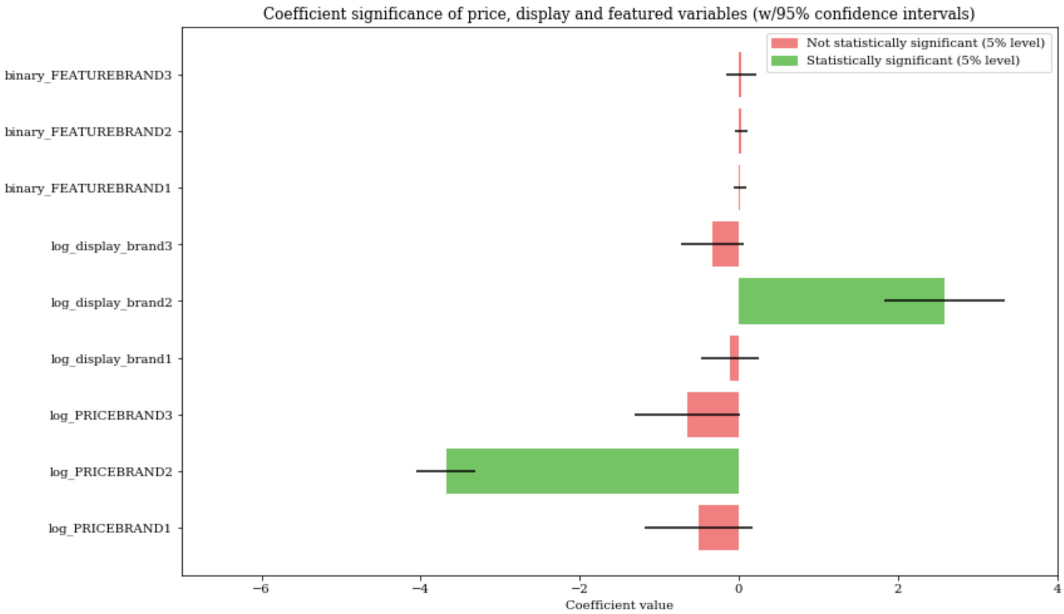

Figure 4: Brand 2 key model coefficients with confidence intervals

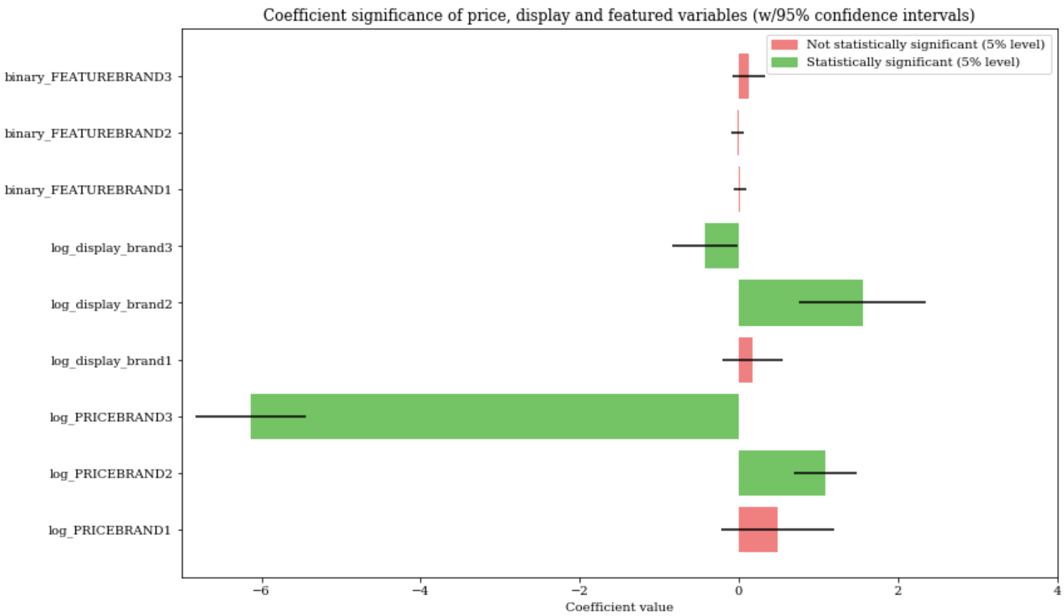

Figure 5: Brand 3 key model coefficients with confidence intervals

magnitude of the coefficient which gives confidence of the sign and relative magnitude of these coefficients.

The cross-brand price elasticities are much lower than the own-brand price elasticities. Indicating consumers are less sensitive to competitor pricing and use any price discounts to stock up on their preferred brand of beer (forward purchase effect).

4.2 Display

The own brand display coefficients are 0.674, 2.583, -0.429 for each brand respectively. This implies that if the percentage of SKUs on display for each brand is increased by 1% (note this is not the same as an increase by 1 *percentage point*), then the unit sales for the week are increased by 0.674% and 2.583% for brands 1 and 2 whereas the unit sales are decreased by 0.429% for brand 3. Display promotions are therefore most effective for brand 2 with a significant sales uplift when a greater percentage of SKUs are on display. Display promotions are less effective for brand 1 and actually detrimental for brand 3. Brand 3 is the least popular of the three brands in terms of unit sales which may explain why customers may not respond well to the promotion.

4.3 Feature

The feature variables in the model are binary and therefore their coefficients are interpreted differently to the price and display variables. The effect on unit sales of the *binary_FEATUREBRAND** variables is equal to $e^{coefficient}$. The own brand feature coefficients for brand 1, 2 and 3 are 0.094, 0.033, 0.123 respectively. However, only brand 1's coefficient is statistically significant. Therefore, if brand 1 is featured during the week then unit sales are increased by approximately 9.9% ($e^{0.094} = 1.099$). The lower 95% confidence interval for this coefficient is greater than 0, therefore it can be concluded that featuring brand 1 has a positive effect on sales.

The own brand coefficients for brand 2 and 3 are not statistically significant but both are positive. This suggests featuring these brands in the week has a positive impact on sales as well, however, we can not be as confident in the magnitude of the effect. The low confidence in these coefficients may be due to the fact that for brands 2 and 3 a lower percentage of SKUs were featured compared to brand 1 (figure 1). This information was lost when converting to a binary variable therefore the effect of feature promotions on brands 2 and 3 is harder to discern.

5 Conclusions

The SCAN*PRO model can be used to estimate the unit sales of competing beer brands with good accuracy and consistency. Seasonality is the largest contributing factor to unit sales, however, price, display and feature promotional activity is also statistically significant.

5.1 Management Recommendations

The following recommendations can be made to Dominick's store manager:

- Use 'feature' advertising to promote brand 1 preferentially.
  - Feature promotions are most effective for brand 1 with a potential 9.9% sales uplift in the weeks brand 1 is featured. Feature promotions for brand 2 and 3 are not as effective.
- Combine display promotions with regular price reductions for brand 2.
  - Display advertising is most beneficial for brand 2 with an increase in unit sales of 2.5% for every percentage point increase in SKUs on display. This should be combined with regular price reductions which could increase sales by a further 3.7% for every 1% reduction in price.
- Only utilise regular price discounts to promote brand 3.
  - Brand 3 customers are most price sensitive. Decreasing prices of brand 3 by 1% can increase unit sales by 6.74%. Brand 3 is a less popular brand of beer and does not respond well to display or feature advertising. Therefore, regular price discounting will have the greatest effect for increasing unit sales.

5.2 Model Improvements

Beer sales are likely to be affected by holidays and bank holidays. Holiday dummy variables could be added to the model to indicate whether a bank holiday occurred during the week which would help estimate unit sales for weeks with a sharp increase in demand caused by holidays.

During regression modelling it was observed that there were a number of data points in the sample with high leverage which could have materially affected the model coefficients. These points could be removed from fitting the model to improve the confidence in the model coefficients.

Promotional activity of competing alternative products to beer, such as wine or spirits, may also affect beer sales but were left out of the model. Data on other competing products could help increase the accuracy of the model and improve the store manger's knowledge of interactions between alternative products.

5.3 Future Work

The SCAN*PRO model only addresses the short-term impact of price changes and promotional activity on product demand. It would also be useful for the store manager to understand the long-term impact of promotional activity on future unit sales as a result of the forward and delayed purchase effects that promotions have on customer purchasing behaviour. This can be quantified using VAR and IRFs models (Srinivasan et al. 2004).

Word Count: 2,732

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