# ASSESSING THE EFFECTIVENESS OF PROMOTIONS FOR A FROZEN PIZZA BRAND

Retail and Marketing Analytics

# Contents

## Executive Summary

Sales promotion expenditures have increased significantly over the past 2 decades particularly in the United States and Western Europe. When making promotion decisions, companies must balance the higher marketing budget needed for the promotion and the return in sales that that promotion should provide the company. With increased availability of sales data, models have been developed to analyse and ascertain the effect that promotions such as temporary price cuts, feature advertising and special displays for items.

Tony's Pizza is a popular frozen pizza brand in the United States. Over the last few years, the company has been implementing a series of promotional activities, however, it has not been able to grow as it would like. As such, the marketing executive wants to use data to understand how Tony's flagship pizza product, the pepperoni pizza, fits into the frozen pizza market and the effect that promotions have on the company's sales.

In order to analyse the effect of not only Tony's promotions on its own sales, but also the actions and promotions of its competitors, a SCAN*PRO model is fitted to the data and the parameters of statistical significance identified. These parameters, like the use of feature and display promotion, along with Tony's own price are of statistical significance and can therefore be used to develop an optimal marketing strategy to maximize expected sales. This sales figure can then guide the company as to whether the marketing mix makes sense from a cost point of view.

## Business and Problem Overview

Tony's Frozen Pizza is a popular frozen pizza brand in the United States and in the Kroger supermarket chain it is one of the top four frozen pizza brands. Tony's offers it customers a wide range of frozen pizza options including cheese, pepperoni among other. However, despite its promotions the company has not seen the growth that it had expected. Particularly as promotions continue to account for a larger percentage of its overall marketing budget, the company's executives want to determine whether these efforts are fruitful. Tony's has called on a marketing analytics firm to help it determine how effective its promotions are and how the marketing strategies of its competitors affects its own performance. Tony's has asked that the analytics firm focuses initially on its flagship pepperoni pizza product as it is one of the most popular products that it offers. If the analytics uncovers any indication of how Tony's marketing mix should be optimised and this new marketing strategy is successful, then the company plans to expand this strategy to its other products.

Given the competitive nature of the frozen pizza industry, Tony's wants to get a better understanding of its competitive landscape and how its marketing efforts have been faring over the past few years. Comparing its flagship pepperoni pizza to its competitor's pepperoni pizza, the company seeks answers to the following questions:

1. What effect does each promotional activity have on sales?
2. Which promotional activity is the most effective in increasing unit sales?
3. Do the actions of its competitors affect Tony's sales? If so, how?
4. If Tony were to implement an optimal strategy based on its own promotional data, how would this affect sales? What is the maximum cost that such a promotion could cost and still be profitable?

## Data Overview

The data being used to conduct this analysis is from the dunnhumby data set 'Breakfast at the Frat'. The original data contains sales and promotion information on the top three products of each of the top four brands within four selected categories, mouthwash, pretzels, frozen pizza and boxed cereal. It is time series data on the transactions of different households over a 3-year period including the amount of each product, the price of the product and any marketing strategies being used on the product at the time of purchase. All purchases are transacted at Kroger supermarkets located in 4 states: Texas (TX), Ohio (OH), Kentucky (KY) and Indiana (IN).

| **Variable Name** | **Description** |
|---|---|
| BASE_PRICE | The base price of the item |
| PRICE | The actual price paid for the item |
| UNITS | The number of units purchased at that time by a household |
| SPEND | Total spent by a household on the item |
| UPC | Unique identifying code for each item |
| DISPLAY | Indicates whether the item was part of in-store promotional display at time of purchase |
| TPR_ONLY | Indicates whether the item has a temporary price reduction only |
| FEATURE | Indicates whether the item was part of the in-store circular |
| WEEK_END_DATE | Week ending date |

**TABLE 1: SUMMARY OF VARIABLES USED IN THE DATA**

## Data Pre-Processing

The data underwent thorough processing before exploration and modelling. Firstly, the data needed to be filtered for the frozen pizza brands that served peperoni pizza. Only 3 brands that had pepperoni pizza products were included as the other brand had no transactional data for such and therefore would not contribute to the analysis of the market.

1. Transactions data for each brand was separated
2. For each of the separate data sets, transactions were grouped by the week and the state in which it was processed.
3. Sales, price and promotional data was aggregated for the weekly transactions.
4. The brand separated data sets were merged by week and by the state code

Despite there not being any missing data in the original data set, some missing values arose during the transformation and merging process. In the first case, transactions for competitor 1, King's Pizza, did not arise till 2010, 1 year after the transaction data arrived. To account for this, the first year of data was removed form the data set. There were also missing values from promotions, price and sales data that arose if no transactions were completed in any given week in a particular state. In this case, missing data was replaced with 0 to account for the fact that there was no sale for that product in the given week and state.

## Exploratory Data Analysis

### Overview of Tony's Peperoni Pizza Sales

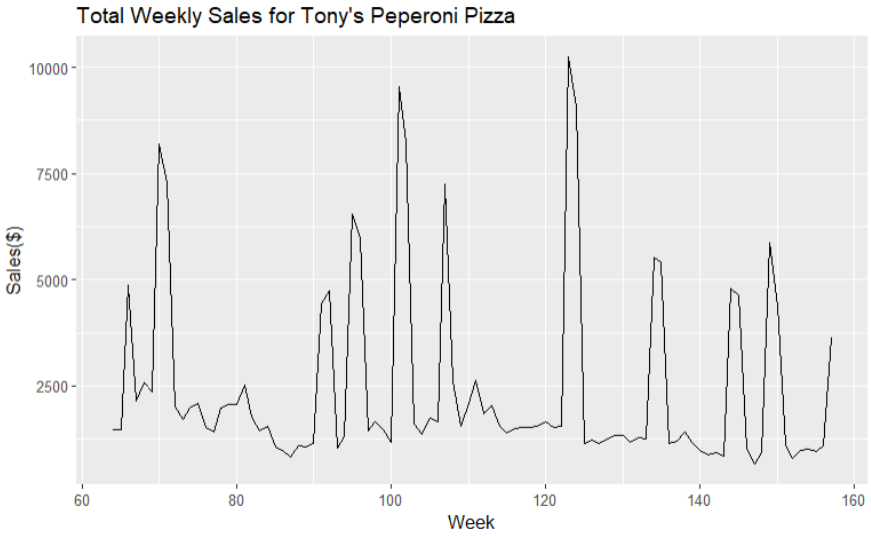


**FIGURE 1: GRAPH SHOWING WEEKLY SALES FOR TONY'S PEPERONI PIZZA**

Overall, the sales of Tony's Peperoni Pizza, does not seem to have a significant trend. Following a time series decomposition, there does seem to be a bit of weekly seasonality in the data and the significance of this seasonality will be tested later. Nonetheless, the distribution of the sales in each week is largely random. Weekly sales in on average $1,500 but has been as high as $15,454.30 and as low as $621.70.

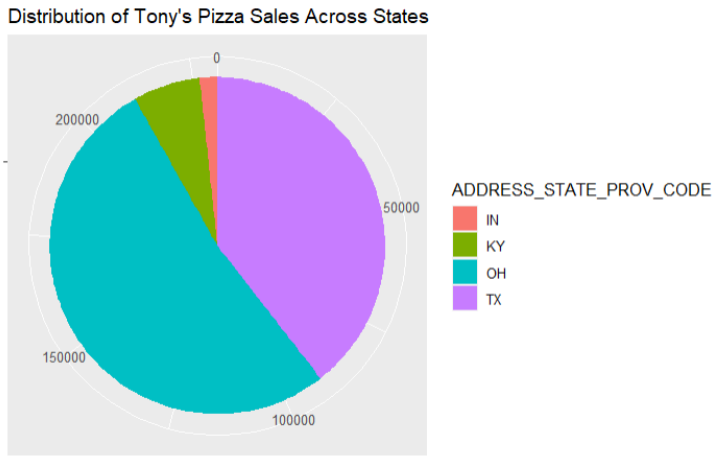


FIGURE 2: PIE CHART ILLUSTRATING THE DISTRIBUTION OF SALES AMONG THE 4 STATES

Within the Kroger supermarket chain, Tony's earns around half of its pepperoni pizza earnings in Ohio with another 45% of sales coming from Texas. The remainder is distributed between Kentucky and Indiana.

## Distribution of Prices Over the 3-year Period

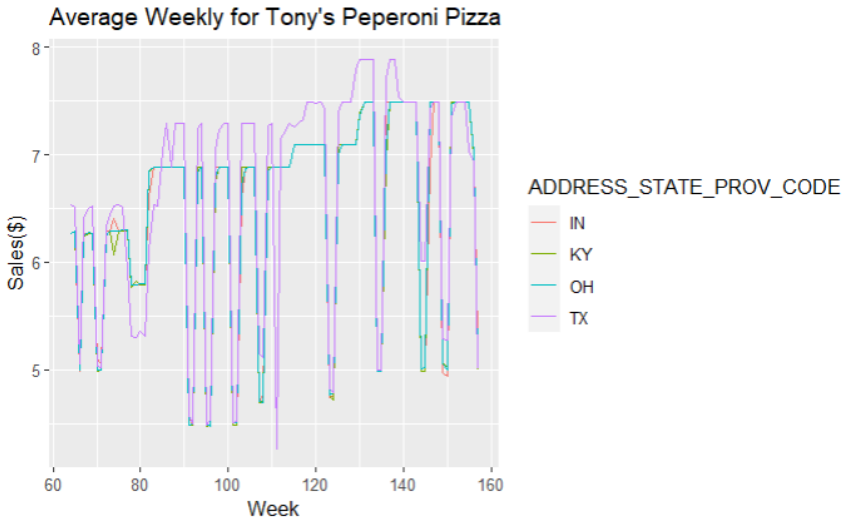


FIGURE 3: WEEKLY AVERAGE PRICE OF TONY'S PEPERONI PIZZA

The weekly price of Tony's Pizza is highly variable. Throughout the three years, the price has been between $4.01 and $7.71. It should be noted that within the last year, the price has seen an increasing trend with similar amount of variability. While all stores follow the same general price trend, the Texas stores at times seems to have higher average prices than the others.

Relationship between Price and Sales for Tony's Peperoni Pizza

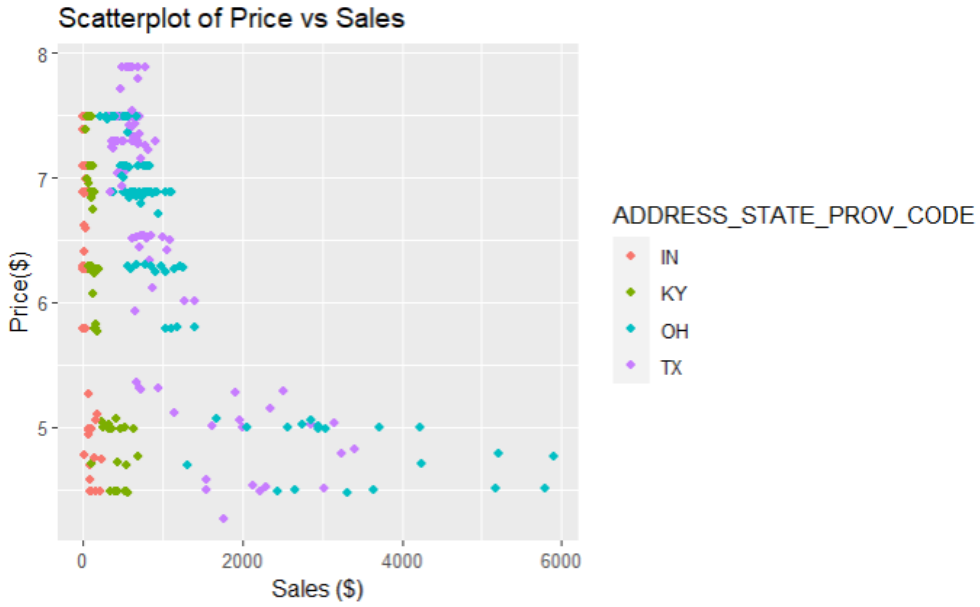


FIGURE 4: PRICE ELASTICITY IN EACH STATE

Sales at the Kentucky and Indiana stores seem to be price inelastic; that is a change in price does not significantly affect sales. Thus is a trend line was drawn between the sales and price for both sets of stores, the line would be straight, vertical. On the other hand, the Ohio and Texas locations show elastic demand whereby as price falls, sales increases.

Pizza Sales for All Pizza Brands

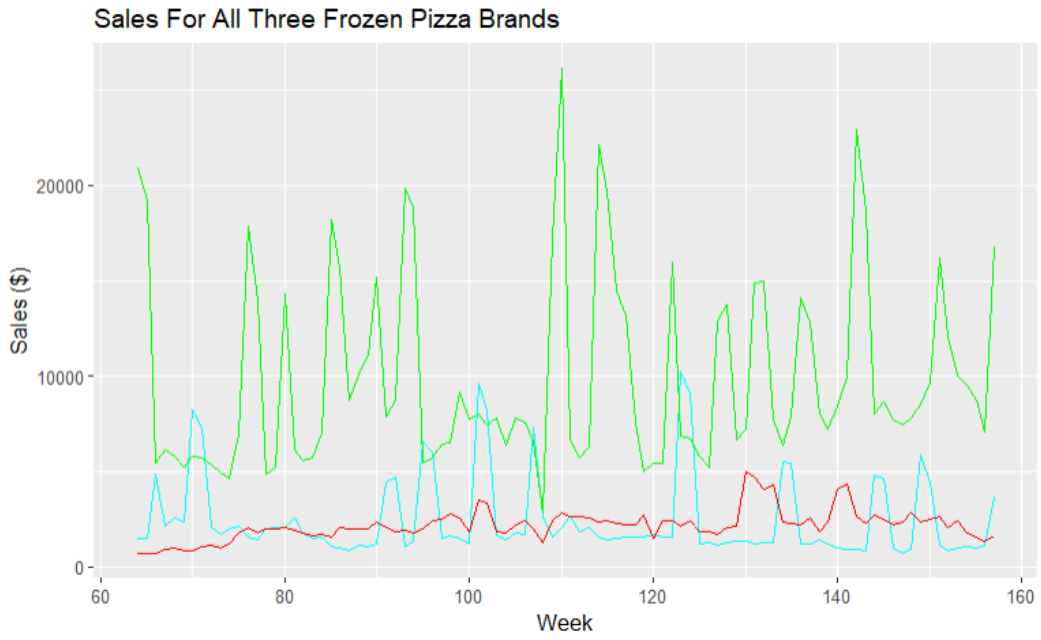


**FIGURE 5: PEPERONI PIZZA SALES FOR ALL THREE BRANDS**

In this plot, the light blue line represents sales of Tony's, the green line represents sales of competitor 2, Tombstone's Digiorno pizza, and the red line is sales of competitor 1, King's. From the plot, it is safe to conclude that Digiorno's pizza has the largest market share of the three competitors with its sales being consistently higher than both Tony's and King's. Digiorno's sales, similarly, to what was identified earlier with Tony's pizza sales, is highly varied. Nonetheless, its sales sits comfortable higher than its other two competitors. Kings seems to be the smallest of the three companies, however, over the years that is a generally increasing trend in the total sales for the company.

Effect of Promotional Activity on Tony's Peperoni Pizza Sales

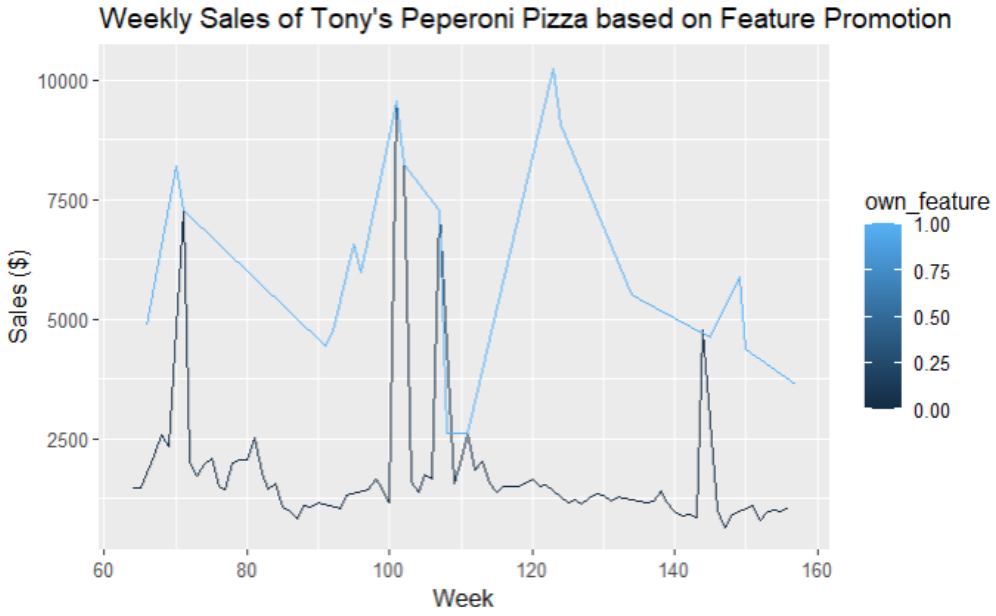


**FIGURE 6: WEEKLY PEPERONI PIZZA SALES BASED ON IN-STORE CIRCULAR**

Tony's Pizza was featured in the in-store circular for 21 out of the 98 weeks under consideration. The light blue line depicts sales for the weeks that Tony's Peperoni Pizza was featured in the in-store circular while the dark blue line represents sales for the weeks that it was not. There is a clear separation between the sales in each of the scenarios, with sales when the pizza is featured being significantly larger than when it is not. This is an indication that being featured in the in-store circular is likely to have a significant positive impact on sales.

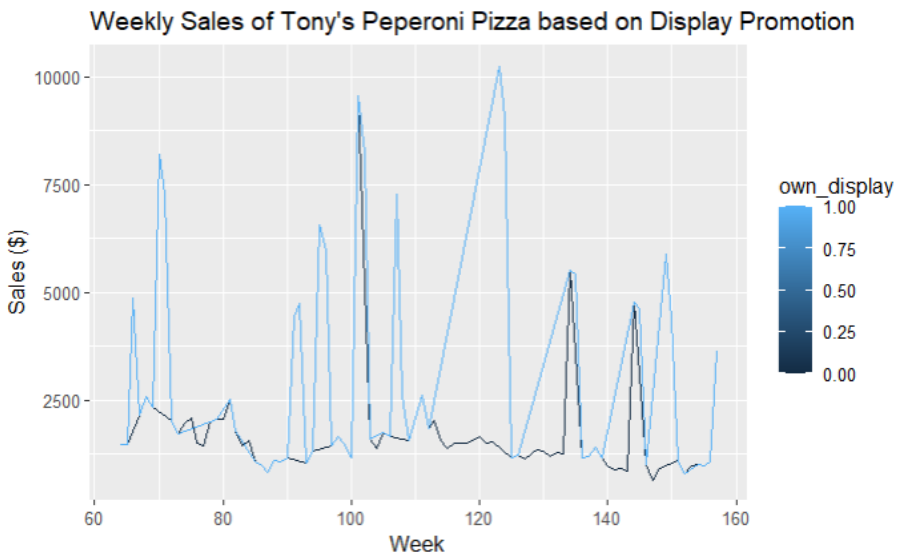


**FIGURE 7: WEEKLY PEPERONI PIZZA SALES BASED ON IN-STORE DISPLAY**

Tony's pizza was on display in some part of the store for 65 of the 98 weeks. The light blue line depicts the sales when the pizza was on display while the dark blue line shows when it was not on display. There is a distinction between sales when the pizza is on display versus when it is not with the sales when on display seeming higher then when it is not on display.

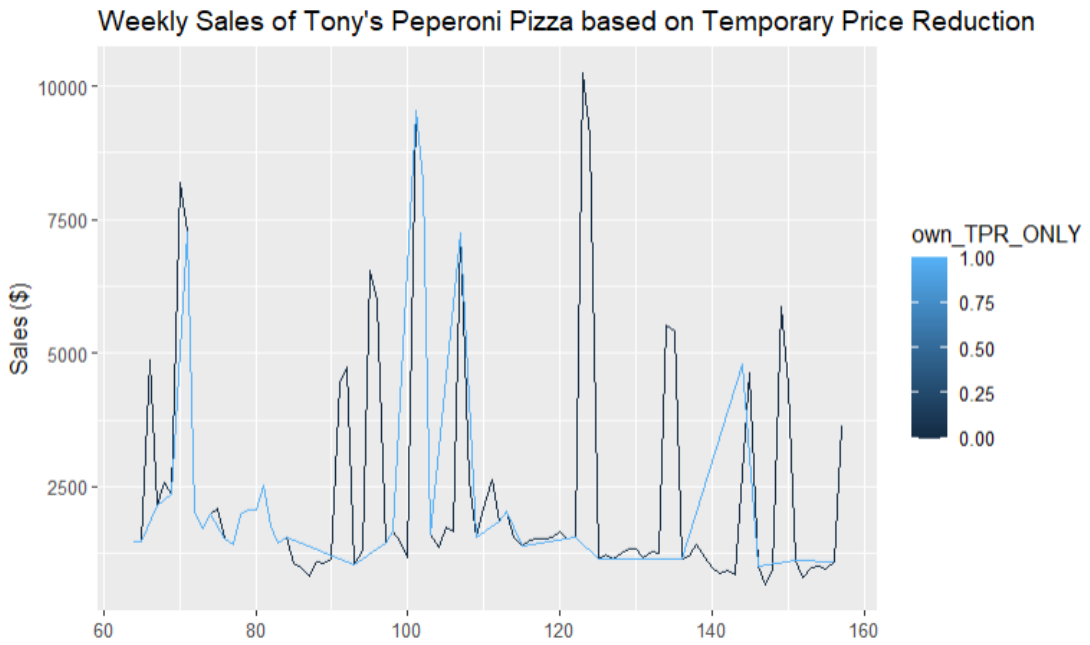


**FIGURE 8: WEEKLY PEPERONI PIZZA SALES BASED ON TPR**

A Temporary Price Reduction was implemented for roughly one-third of the time (38 out of the 98 weeks). Based on the graph, there is little distinction in the sales during a temporary price reduction versus when there is not, the light blue verses the dark blue line. Thus, from initial visual analysis it seems as if a temporary price reduction is not an effective promotional technique.

## Analysis of the Effect of Promotions and Competitor Action on Tony's Pizza Sales - SCAN*PRO Model

In order to objectively quantify the effect of the company's own promotions and other activities conducted by its competitors on sales and separate these effects, a SCAN*PRO model was fitted to the data. This SCAN*PRO model was developed on state-level, weekly unit sales data, accommodating temporary price cuts, display and feature advertising for both Tony's pizza and its competitors. It also considered the price and sales level for Tony's and its competitors and accounted for weekly seasonality. The model was also expanded to include interaction terms between the state of the transaction and promotional activity to determine if the effect of the marketing strategy may differ my state.

The original model was statistically significant at the 5% level (p-value of $< 2.2\ e^{-16}$) and based on the R-squared value was able to account for approximately 96.5% of the variation in the sales data. This model, the full model, was complex but complete. It contained 80 variables and the intercept term and runs the risk not having accurate forecasts due to the variability being considered from the numerous parameters.

In order to make the model simpler, and possible increase the accuracy of the model, backward selection was used, using the Alkine Information Criterion (AIC), to determine which variables are statistically significant to the model and therefore useful in understanding Tony's weekly sales data. The reduced model fitted to the data is:

$$Weekly\ Sales(units)$$

$$= 413.81 * (Comp2_{price})^{0.038} * (own_{price})^{-3.715} * (Comp1_{sales})^{0.038}$$
$$* (1.752)^{own_{feature}} * (1.14)^{comp2\_TPR\_ONLY} * (1.17)^{own_{display}}$$
$$* (34.398)^{KY} * (285.63)^{OH} * (1.96)^{TX} * (own\_price)^{-1.11*KY}$$
$$* (own\_price)^{-0.523*OH} * (own\_price)^{1.412*TX} * (0.543)^{own_{feature}*KY}$$
$$* (0.621)^{own\_feature*OH} * (0.964)^{own\_feature*TX}$$
$$* (seasonality\ parameters)$$

This reduced model is also statistically significant with a p-value very close to 0 (p-value: <2.2 $e^{-16}$). Based on the R-squared value, this reduced model can explain around 96.3% of the total variation in sales data, which is comparable with the performance of the full model. The adjusted R-squared of this model is also just under 95.5% which implied that even after accounting for the number of parameters that the model includes, this reduced model is 'better' at explaining variation in Tony's sales. This model shows that, after adjusting for weekly seasonality:

- The cross-price elasticity of demand between Digiorno's pizza (competitor 2) and Tony's pizza is 0.038. This implies that a 1% increase in the price of Digiorno's pizza is estimated to be accompanied by a 0.038% increase Tony's pizza sales. This change, though significant is negligible for practical purposes.
- Tony's and King's pizza sales tend to move with one another. A 1% increase in King's pizza sales is estimated to be accompanied by a 0.038% increase in Tony's pizza sales.
- The effect of a temporary price reduction by Digiorno's positively impacts King's pizza sales with the effect measured at 1.14. Thus, if Digiorno were to implement a temporary price reduction, it would be estimated that King's pizza sales would be 14% higher than if the TPR was not conducted.

- Tony's own in-store displays can contribute 17% higher sales than if the display were not shown in store.
- Temporary price reduction of Tony's pizza alone does not significantly impact sales.

The effect of being featured in the in-store circular, however, differs by state. The feature effect has its highest impact in Indiana when an in-store circular feature is estimated to add an additional 75.2% in sales, versus if it were not featured. This is closely followed by the effect in Texas which would be an estimated 1.69. Thus, feature promotion in list state is expected to lead to 69% higher sales than if not implemented. In Ohio, this feature promotion has a significantly smaller effect on sales with only an estimated 8.8% increase if the feature promotion were used in this state. However, in Kentucky, feature promotion is estimated to negatively impact sales with an expected 4.9% fall in unit sales if feature promotion were used.

The price elasticity of demand also varies by state. In Indiana, a 1% increase in price is expected to contribute to a 3.7% fall off in prices. This elasticity effect is stronger in Kentucky and Ohio with a 1% increase in price resulting in a 4.8% and 4.2% fall in sales respectively. However, in Texas, the price elasticity is the smallest with a 1% increase in price resulting in only a 2.3% fall in sales.

## Insights and Recommendations

- Based on the model, generally, promotional activity by competitor's does not affect Tony's pizza sales. A temporary price reduction of Digiorno's pizzas, however, does have a statistically and economically significant impact on sales with the price promotion estimated to result in a 14% increase in overall sales.
- In Indiana and Texas, feature promotion would be considered as the most effective promotion technique, while display promotions would be most effective in Kentucky and Ohio.
- Across all states, lower prices should result in higher sales levels, however this decreasing price strategy would be most effective in Indiana and least effective in Texas.

Based on the results of the model as described above, the optimal marketing strategy is:

- Use in-store displays in all four states as this positively contributes towards higher sales.
- Only use feature promotion in Indiana, Texas and Ohio as this type of promotion positively contributes towards sales in these states. In Kentucky, on the other hand, feature promotion is likely to be a loss-making activity.
- In Texas and Ohio, where demand is more price elastic, a reducing price strategy may be more appropriate and thus the increase in unit sales from a fall in price would result in profit.
- If possible, there could be a strategic alliance between Tony's and Digiorno's. Since a temporary price reduction in Digiorno's contributes to higher sales of Tony's, both

companies could collaborate in a promotion involving TPR and it should positively impact both companies.

| | Unit Sales | | |
|---|---|---|---|
| State | Optimal Marketing Mix | All Marketing Options | No Marketing |
| Indiana | 10.6 | 5.72 | 5.31 |
| Kentucky | 51.71 | 35.74 | 32.6 |
| Ohio | 424.01 | 374.91 | 366.27 |
| Texas | 355.13 | 164.06 | 166.05 |
| All | 841.45 | 580.43 | 570.23 |

**TABLE 2: EXPECTED UNIT SALES UNDER THREE MARKETING SCENARIOS**

The table above shows the expected sales under three marketing scenarios. In the Optimal marketing mix, the strategies described above are employed with the display promotion used and features only used in Indiana, Ohio and Texas. This case has the highest overall expected weekly sales of 841.45 units. If all marketing options were used in every state, temporary price reduction, features and instore displays, sales would be estimated at only 580.43 units and if no marketing was used at all, sales would be 570.23 units. Based on the model, therefore, the best marketing mix is to use display promotion in all states while restricting in-store circulars to only Indiana, Kentucky and Texas.

| | Weekly Sales ($) | |
|---|---|---|
| State | Optimal Mix | No Marketing |
| Indiana | $ 4,239.79 | $ 2,878.22 |
| Kentucky | $ 4,183.93 | $ 2,850.24 |
| Ohio | $ 3,925.38 | $ 2,687.24 |
| Texas | $ 1,775.65 | $ 830.25 |
| All | $ 14,124.75 | $ 9,245.95 |

**TABLE 3: EXPECTED WEEKLY SALES ($) UNDER DIFFERENT MARKETING STRATEGIES**

Using the last average price in each state, the optimal mix would generate close to $4,900 in additional weekly revenue. Therefore, the budget for this marketing mix should not exceed $253,700 for the year for this marketing mix to be cost effective, profitable.

# Appendix

```
Call:
lm(formula = log_own_units ~ log_comp1_price + log_comp1_sales +
    comp1_feature + comp1_display + comp1_TPR_ONLY + log_comp2_sales +
    log_comp2_price + comp2_feature + comp2_display + comp2_TPR_ONLY +
    log_own_price + own_display + own_feature + own_TPR_ONLY +
    ADDRESS_STATE_PROV_CODE + ADDRESS_STATE_PROV_CODE:log_own_price +
    ADDRESS_STATE_PROV_CODE:own_display + ADDRESS_STATE_PROV_CODE:own_TPR_ONLY +
    ADDRESS_STATE_PROV_CODE:own_feature + as.factor(week_of_year),
    data = final_df)

Residuals:
     Min       1Q   Median       3Q      Max
-1.18756 -0.17951 -0.00484  0.18968  0.93509

Coefficients:
                                        Estimate Std. Error t value Pr(>|t|)
(Intercept)                            5.6855118  1.8702790   3.040  0.00258 **
log_comp1_price                       -0.1596177  0.4855684  -0.329  0.74260
log_comp1_sales                        0.0359454  0.0163771   2.195  0.02897 *
comp1_feature1                         0.1116522  0.2545429   0.439  0.66125
comp1_display1                         0.0647932  0.1065039   0.608  0.54342
comp1_TPR_ONLY1                        0.0133797  0.1109180   0.121  0.90407
log_comp2_sales                       -0.0230889  0.0925903  -0.249  0.80325
log_comp2_price                        1.3152359  0.4223363   3.114  0.00203 **
comp2_feature1                         0.0787081  0.1327983   0.593  0.55385
comp2_display1                        -0.0064150  0.0571444  -0.112  0.91069
comp2_TPR_ONLY1                        0.1546742  0.0856285   1.806  0.07190 .
log_own_price                         -3.4815048  0.5203332  -6.691 1.14e-10 ***
own_display1                           0.2554913  0.1002848   2.548  0.01136 *
own_feature1                           0.5991753  0.2004038   2.990  0.00303 **
own_TPR_ONLY1                          0.4205393  0.4367620   0.963  0.33642
ADDRESS_STATE_PROV_CODEKY              4.1468047  1.3558911   3.058  0.00243 **
ADDRESS_STATE_PROV_CODEOH              5.6568359  1.3906883   4.068 6.13e-05 ***
ADDRESS_STATE_PROV_CODETX              1.3559186  1.4055800   0.965  0.33551
as.factor(week_of_year)2               0.1053966  0.2398218   0.439  0.66064
as.factor(week_of_year)3               0.2092681  0.2599341   0.805  0.42143
as.factor(week_of_year)4              -1.2092325  0.2594736  -4.660 4.82e-06 ***
as.factor(week_of_year)5               0.2061972  0.2690556   0.766  0.44408
as.factor(week_of_year)6               0.4107084  0.2386637   1.721  0.08634 .
as.factor(week_of_year)7              -0.4989826  0.2418730  -2.063  0.04000 *
as.factor(week_of_year)8               0.1573208  0.2497290   0.630  0.52921
as.factor(week_of_year)9              -0.2866812  0.2426939  -1.181  0.23847
as.factor(week_of_year)10              0.4316574  0.2404736   1.795  0.07369 .
as.factor(week_of_year)11             -0.2138996  0.2275906  -0.940  0.34808
as.factor(week_of_year)12             -0.1259064  0.2033818  -0.619  0.53636
as.factor(week_of_year)13             -0.1673750  0.2059409  -0.813  0.41704
as.factor(week_of_year)14             -0.0694000  0.1930484  -0.359  0.71949
as.factor(week_of_year)15             -0.0631304  0.2007019  -0.315  0.75333
as.factor(week_of_year)16              0.1496487  0.2014506   0.743  0.45817
as.factor(week_of_year)17             -0.0440545  0.1992475  -0.221  0.82517
as.factor(week_of_year)18              0.3497885  0.1916329   1.825  0.06898 .
as.factor(week_of_year)19              0.3969426  0.2059233   1.928  0.05488 .
as.factor(week_of_year)20             -0.0341551  0.1994904  -0.171  0.86418
as.factor(week_of_year)21             -0.4952508  0.2023412  -2.448  0.01497 *
as.factor(week_of_year)22             -0.1642330  0.2090235  -0.786  0.43268
```

```
as.factor(week_of_year)23                -0.3780208  0.1942186  -1.946  0.05258 .
as.factor(week_of_year)24                -0.1528338  0.1971974  -0.775  0.43895
as.factor(week_of_year)25                -0.0636307  0.1983437  -0.321  0.74859
as.factor(week_of_year)26                -0.3064024  0.2335965  -1.312  0.19067
as.factor(week_of_year)27                -0.3504753  0.2285369  -1.534  0.12623
as.factor(week_of_year)28                 0.0655897  0.2317404   0.283  0.77735
as.factor(week_of_year)29                -0.3957184  0.2282042  -1.734  0.08397 .
as.factor(week_of_year)30                -0.0851136  0.2024148  -0.420  0.67444
as.factor(week_of_year)31                -0.1450898  0.2088008  -0.695  0.48769
as.factor(week_of_year)32                -0.4074186  0.1972368  -2.066  0.03975 *
as.factor(week_of_year)33                -0.0285839  0.2015712  -0.142  0.88733
as.factor(week_of_year)34                -0.0883273  0.1988442  -0.444  0.65723
as.factor(week_of_year)35                -0.2038264  0.2189277  -0.931  0.35262
as.factor(week_of_year)36                -0.4621388  0.2305630  -2.004  0.04596 *
as.factor(week_of_year)37                -0.2654818  0.2370791  -1.120  0.26372
as.factor(week_of_year)38                -0.1644492  0.2072954  -0.793  0.42825
as.factor(week_of_year)39                -0.3024191  0.2051066  -1.474  0.14145
as.factor(week_of_year)40                 0.0284702  0.2345814   0.121  0.90349
as.factor(week_of_year)41                 0.0228338  0.2035561   0.112  0.91076
as.factor(week_of_year)42                -0.1479055  0.2029686  -0.729  0.46677
as.factor(week_of_year)43                -0.2776651  0.1973027  -1.407  0.16041
as.factor(week_of_year)44                -0.2815082  0.2000508  -1.407  0.16044
as.factor(week_of_year)45                 0.0557609  0.2011802   0.277  0.78185
as.factor(week_of_year)46                -0.0645593  0.2049705  -0.315  0.75301
as.factor(week_of_year)47                -0.0480624  0.2000083  -0.240  0.81027
as.factor(week_of_year)48                -0.3159538  0.2047373  -1.543  0.12387
as.factor(week_of_year)49                 0.0885214  0.2155188   0.411  0.68157
as.factor(week_of_year)50                -0.0008711  0.2079314  -0.004  0.99666
as.factor(week_of_year)51                -0.0214359  0.1964082  -0.109  0.91317
as.factor(week_of_year)52                -0.1976310  0.1982123  -0.997  0.31956
log_own_price:ADDRESS_STATE_PROV_CODEKY -1.3903003  0.6905000  -2.013  0.04499 *
log_own_price:ADDRESS_STATE_PROV_CODEOH -1.0738037  0.6794650  -1.580  0.11511
log_own_price:ADDRESS_STATE_PROV_CODETX  1.1217681  0.6808482   1.648  0.10052
own_display1:ADDRESS_STATE_PROV_CODEKY  -0.1780471  0.2727242  -0.653  0.51437
own_display1:ADDRESS_STATE_PROV_CODEOH  -0.2056969  0.1642455  -1.252  0.21144
own_display1:ADDRESS_STATE_PROV_CODETX  -0.1182547  0.1409944  -0.839  0.40232
own_TPR_ONLY1:ADDRESS_STATE_PROV_CODEKY -0.3340556  0.4804959  -0.695  0.48747
own_TPR_ONLY1:ADDRESS_STATE_PROV_CODEOH -0.4518770  0.4611975  -0.980  0.32801
own_TPR_ONLY1:ADDRESS_STATE_PROV_CODETX -0.3768660  0.4507928  -0.836  0.40384
own_feature1:ADDRESS_STATE_PROV_CODEKY  -0.5742047  0.3124723  -1.838  0.06714 .
own_feature1:ADDRESS_STATE_PROV_CODEOH  -0.5412393  0.2866239  -1.888  0.05998 .
own_feature1:ADDRESS_STATE_PROV_CODETX  -0.0679551  0.3036813  -0.224  0.82309
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 0.366 on 290 degrees of freedom
Multiple R-squared:  0.964,     Adjusted R-squared:  0.954
F-statistic: 96.95 on 80 and 290 DF,  p-value: < 2.2e-16
```

**FIGURE 9: FULL SPAN*PRO MODEL FITTED TO THE DATA**

```
Call:
lm(formula = log_own_units ~ log_comp1_sales + log_comp2_price +
    comp2_TPR_ONLY + log_own_price + own_display + own_feature +
    ADDRESS_STATE_PROV_CODE + as.factor(week_of_year) + log_own_price:ADDRESS_STATE_PROV_CODE +
    own_feature:ADDRESS_STATE_PROV_CODE, data = final_df)

Residuals:
     Min       1Q   Median       3Q      Max
-1.25155 -0.17363 -0.00834  0.20463  0.89725

Coefficients:
                                    Estimate Std. Error t value Pr(>|t|)
(Intercept)                         6.025483   1.052577   5.725 2.49e-08 ***
log_comp1_sales                     0.037743   0.015267   2.472 0.013976 *
log_comp2_price                     1.169978   0.253585   4.614 5.84e-06 ***
comp2_TPR_ONLY1                     0.131192   0.074627   1.758 0.079761 .
log_own_price                      -3.715336   0.449166  -8.272 4.19e-15 ***
own_display1                        0.156793   0.058501   2.680 0.007760 **
own_feature1                        0.561537   0.181929   3.087 0.002211 **
ADDRESS_STATE_PROV_CODEKY           3.538338   1.051685   3.364 0.000865 ***
ADDRESS_STATE_PROV_CODEOH           4.451237   1.054408   4.222 3.21e-05 ***
ADDRESS_STATE_PROV_CODETX           0.674966   1.087080   0.621 0.535132
as.factor(week_of_year)2            0.126504   0.227342   0.556 0.578312
as.factor(week_of_year)3            0.215336   0.238647   0.902 0.367602
as.factor(week_of_year)4           -1.153840   0.226874  -5.086 6.41e-07 ***
as.factor(week_of_year)5            0.187154   0.235495   0.795 0.427392
as.factor(week_of_year)6            0.446631   0.228919   1.951 0.051971 .
as.factor(week_of_year)7           -0.453768   0.227354  -1.996 0.046840 *
as.factor(week_of_year)8            0.218934   0.229313   0.955 0.340468
as.factor(week_of_year)9           -0.258477   0.230512  -1.121 0.263038
as.factor(week_of_year)10           0.439664   0.232435   1.892 0.059501 .
as.factor(week_of_year)11          -0.182684   0.205239  -0.890 0.374115
as.factor(week_of_year)12          -0.102897   0.194522  -0.529 0.597208
as.factor(week_of_year)13          -0.135745   0.195334  -0.695 0.487626
as.factor(week_of_year)14          -0.043819   0.183442  -0.239 0.811368
as.factor(week_of_year)15          -0.039091   0.188196  -0.208 0.835592
as.factor(week_of_year)16           0.155220   0.188792   0.822 0.411623
as.factor(week_of_year)17          -0.031252   0.188615  -0.166 0.868511
as.factor(week_of_year)18           0.387612   0.181622   2.134 0.033629 *
as.factor(week_of_year)19           0.433989   0.189278   2.293 0.022538 *
as.factor(week_of_year)20           0.014262   0.185260   0.077 0.938685
as.factor(week_of_year)21          -0.489418   0.186678  -2.622 0.009189 **
as.factor(week_of_year)22          -0.134886   0.188167  -0.717 0.474023
as.factor(week_of_year)23          -0.351766   0.187310  -1.878 0.061340 .
as.factor(week_of_year)24          -0.120138   0.189687  -0.633 0.526983
as.factor(week_of_year)25          -0.047112   0.188603  -0.250 0.802914
as.factor(week_of_year)26          -0.211586   0.199555  -1.060 0.289853
as.factor(week_of_year)27          -0.210996   0.187459  -1.126 0.261239
as.factor(week_of_year)28           0.178655   0.201740   0.886 0.376548
as.factor(week_of_year)29          -0.308446   0.195934  -1.574 0.116473
as.factor(week_of_year)30          -0.030922   0.185082  -0.167 0.867424
as.factor(week_of_year)31          -0.103334   0.191226  -0.540 0.589333
as.factor(week_of_year)32          -0.361584   0.185356  -1.951 0.052005 .
as.factor(week_of_year)33           0.007218   0.192289   0.038 0.970080
as.factor(week_of_year)34          -0.079062   0.187710  -0.421 0.673911
as.factor(week_of_year)35          -0.207781   0.193539  -1.074 0.283859
as.factor(week_of_year)36          -0.440829   0.194666  -2.265 0.024245 *
as.factor(week_of_year)37          -0.214454   0.204744  -1.047 0.295735
as.factor(week_of_year)38          -0.113401   0.197452  -0.574 0.566176
as.factor(week_of_year)39          -0.294788   0.191122  -1.542 0.124016
```

```
as.factor(week_of_year)40                0.071718   0.200574   0.358 0.720918
as.factor(week_of_year)41                0.021691   0.186973   0.116 0.907719
as.factor(week_of_year)42               -0.137233   0.188129  -0.729 0.466281
as.factor(week_of_year)43               -0.254071   0.184947  -1.374 0.170532
as.factor(week_of_year)44               -0.274334   0.183332  -1.496 0.135593
as.factor(week_of_year)45                0.072987   0.183053   0.399 0.690379
as.factor(week_of_year)46               -0.066091   0.188420  -0.351 0.726007
as.factor(week_of_year)47                0.018378   0.185740   0.099 0.921248
as.factor(week_of_year)48               -0.248211   0.184994  -1.342 0.180687
as.factor(week_of_year)49                0.120613   0.190744   0.632 0.527648
as.factor(week_of_year)50                0.044964   0.184396   0.244 0.807516
as.factor(week_of_year)51               -0.039698   0.185210  -0.214 0.830424
as.factor(week_of_year)52               -0.198872   0.185752  -1.071 0.285186
log_own_price:ADDRESS_STATE_PROV_CODEKY -1.108154   0.548085  -2.022 0.044066 *
log_own_price:ADDRESS_STATE_PROV_CODEOH -0.523579   0.548303  -0.955 0.340383
log_own_price:ADDRESS_STATE_PROV_CODETX  1.418376   0.560402   2.531 0.011878 *
own_feature1:ADDRESS_STATE_PROV_CODEKY  -0.609674   0.235350  -2.591 0.010045 *
own_feature1:ADDRESS_STATE_PROV_CODEOH  -0.476700   0.233409  -2.042 0.041981 *
own_feature1:ADDRESS_STATE_PROV_CODETX  -0.036773   0.242376  -0.152 0.879509
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 0.3607 on 304 degrees of freedom
Multiple R-squared:  0.9633,    Adjusted R-squared:  0.9553
F-statistic: 120.9 on 66 and 304 DF,  p-value: < 2.2e-16
```

**FIGURE 10: REDUCED SCAN*PRO MODEL FROM BACKWARD SELECTION**

```
Call:
lm(formula = log_own_units ~ log_comp1_price + log_comp2_sales +
    comp2_TPR_ONLY + log_own_price + own_display + own_feature +
    ADDRESS_STATE_PROV_CODE + ADDRESS_STATE_PROV_CODE:log_own_price +
    ADDRESS_STATE_PROV_CODE:own_feature, data = final_df)

Residuals:
     Min       1Q   Median       3Q      Max
-1.49528 -0.19425  0.03666  0.25527  1.00899

Coefficients:
                                          Estimate Std. Error t value Pr(>|t|)
(Intercept)                               10.20175    1.02034   9.998  < 2e-16 ***
log_comp1_price                           -0.38667    0.28207  -1.371 0.171291
log_comp2_sales                           -0.13798    0.04289  -3.217 0.001414 **
comp2_TPR_ONLY1                           -0.05959    0.06622  -0.900 0.368821
log_own_price                             -4.07793    0.48012  -8.493 5.58e-16 ***
own_display1                               0.21399    0.06331   3.380 0.000805 ***
own_feature1                               0.47734    0.19662   2.428 0.015691 *
ADDRESS_STATE_PROV_CODEKY                  4.15871    1.24077   3.352 0.000890 ***
ADDRESS_STATE_PROV_CODEOH                  5.45919    1.25754   4.341 1.85e-05 ***
ADDRESS_STATE_PROV_CODETX                  0.87028    1.25612   0.693 0.488866
log_own_price:ADDRESS_STATE_PROV_CODEKY   -1.30413    0.64830  -2.012 0.045014 *
log_own_price:ADDRESS_STATE_PROV_CODEOH   -0.72041    0.65170  -1.105 0.269718
log_own_price:ADDRESS_STATE_PROV_CODETX    1.59857    0.64456   2.480 0.013598 *
own_feature1:ADDRESS_STATE_PROV_CODEKY    -0.72453    0.27831  -2.603 0.009620 **
own_feature1:ADDRESS_STATE_PROV_CODEOH    -0.54494    0.27744  -1.964 0.050294 .
own_feature1:ADDRESS_STATE_PROV_CODETX     0.06888    0.27605   0.250 0.803113
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 0.4307 on 355 degrees of freedom
Multiple R-squared:  0.9389,    Adjusted R-squared:  0.9363
F-statistic: 363.6 on 15 and 355 DF,  p-value: < 2.2e-16
```

**FIGURE 11: SCAN*PRO MODEL WITHOUT WEEKLY SEASONALITY USED FOR PREDICTION**

| | Weekly Unit Sales | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| | Optimal Marketing Mix | | | All Marketing Options | | | No Marketing | | |
| | Fit | Lower Bound | Upper Bound | Fit | Lower Bound | Upper Bound | Fit | Lower Bound | Upper Bound |
| **Indiana** | 10.6 | 4.15 | 27.09 | 5.72 | 2.14 | 15.34 | 5.31 | 2.01 | 14.04 |
| **Kentucky** | 51.71 | 20.33 | 131.5 | 35.74 | 13.95 | 91.59 | 32.6 | 12.98 | 81.88 |
| **Ohio** | 424.01 | 175.75 | 1022.99 | 374.91 | 152.09 | 924.17 | 366.27 | 148.81 | 901.52 |
| **Texas** | 355.13 | 147.87 | 852.9 | 164.06 | 66.14 | 406.92 | 166.05 | 66.98 | 411.64 |
| **All** | 841.45 | 348.1 | 2034.48 | 580.43 | 234.32 | 1438.02 | 570.23 | 230.78 | 1409.08 |

**TABLE 4: WEEKLY UNIT SALES UNDER VARYING MARKETING SCENARIOS USING A PREDICTION INTERVAL**

## References

Leeflang, P. S. H., Heerde, H. J. V., & Wittink, D. R. (2002). *How promotions work: Scan*pro-based evolutionary model building*. CORE. Retrieved April 22, 2022, from https://core.ac.uk/display/34703636

Data set: Breakfast at the Frat, dunnhumby: Source Files - dunnhumby