MKT 680: Marketing Mix Models

Understanding Drivers of Mahou San Miguel's Sales

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Executive Summary

With the large amount of sales growing towards beers and other alcoholic beverages in Europe and Portugal, it is important for grocery stores and beer producers to understand the impact of marketing practices on consumer behavior and purchases. It is essential to break down the process of marketing analytics to its individual components to understand the impact of each vehicle and also the expected return on investment from sales.

We will be helping Mahou San Miguel and Pernalonga to understand how their various marketing efforts towards the sale of three beer products is achieved using various marketing vehicles such as TV, radio, flyers, store display, web display, and paid search over and above their base level of sales. We will start by disintegrating each of these above components and studying their individual impact on sales while also considering weekly price changes and any seasonality within the data. Finally, we will be running two different models - logit and multiplicative to study the impact of these marketing efforts on sales and visualize them to highlight which vehicles could be useful to continue investing in the future and which vehicles might not be as fruitful. The goal of this analysis is to allow San Miguel to identify what tools and efforts provide significant results towards total revenue for their prime beer products.

Introduction

Background

Beer is the second most consumed alcoholic beverage in the world ahead of the wine and behind the spirits. The Europe beer market was valued at $138,649 million in 2017 and is projected to reach $159,687 million by 2025. Each country in the region has their national beer but branded beer such as Guinness (Dublin), Heineken (Amsterdam) and Tuborg (Copenhagen) are some of the most profitable ones that are popular in the region. Rise in disposable income, changes in lifestyle, and wide acceptance of beer as a refreshment beverage drive the Europe beer market growth.

Focusing in on Lunitunia, Portugal, beer experienced record sales in 2017, with annual beer consumption per capita being 51 litres. According to Nielsen, the growth of the category is related to the greater preference among Portuguese consumers for out-of-home consumption, associated with leisure activities. 30% of Portuguese spend their extra money on out-of-home entertainment, compared to 12% in 2013. Another important factor to consider is around promotions, with 70% of beer sales in the retail channel now sold on promotion, compared to 67% the previous year. And so beer consumption in Portugal is markedly seasonal and consumption during the summer months remains key to volume sales.

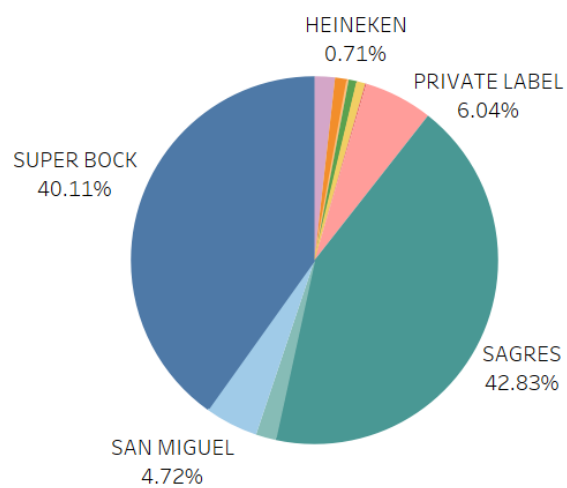
The beer market here is dominated by two companies, Super Bock Group SGPS SA and SCC - Sociedade Central de Cervejas, both with strong shareholder links to global beer companies, respectively Carlsberg and Heineken. Super Bock Group is the market leader in Portugal, holding a market share of 47% with a strong brand portfolio, including brands such as Super Bock, Carlsberg and Somersby. However, Mahou San Miguel, a leading beer brand in Spain founded in 1890, has been trying to increase their sales in Portugal, specifically in Pernalonga Stores. San Miguel offers a variety of products from different flavors of beer to some non-alcoholic or alcohol free beers as well. San Miguel currently utilizes many promotion channels within Pernalonga, from traditional media like TV and Radio to more internet-based promotion channels like email and online ads. Our goal with this project is to see which marketing techniques contribute most to sales so that San Miguel can further invest in these efforts to gain a greater market share and improve revenue growth.

Proposed Approach

Our goal is to understand drivers of Mahou San Miguel's sales. In order to achieve this we will use Market Mix Modeling (MMM) to quantify the impact of several marketing inputs on sales or Market Share. The purpose of using MMM is to understand how much each marketing input contributes to sales, and therefore how much to spend on each marketing input. We will build 3 models, one for each product offered in Pernalonga. After understanding where these products stood in the market, we break down the different drivers of sales (causals) looking specifically at TV and Radio Promotion, List Price and Discounts, Flyers and Store Displays, Email Marketing, and Seasonality and Holidays. Using this information we built 2 model types for each product - Multiplicative Model and Logit Model. To see which model more accurately explained the effect of the causals, we did a full model diagnostic looking at various different statistics to make sure the results were trustworthy; finally enabling us to give Mahou San Miguel some key recommendations on where to further invest their money.

Method

Data Exploration



We began our analysis by trying to understand where San Miguel currently lies in Pernalonga Stores. Beer contributes €1,679,127.67 (13.6%) of total sales at Pernalonga. From the chart we can see that the leading beer brands in Pernalonga stores are Sagres (42.83% market share) and Super Bock (40.11% market share). San Miguel has not been able to achieve this level of success with a 4.72% market share.

San Miguel currently offers 3 different beer products (138936951, 138936952, 138936953) in Pernalonga stores, contributing to 8,745 transactions across all the product types. While San Miguel products are sold throughout the year, most of their foot-traffic comes in the summer months, specifically July. Additionally, they do not usually offer discounts, however, in the off chance they do, it can range upto 30%. Product 138936951 is the most popular product of the 3 which could be attributed to the fact that most discounts that San Miguel does offer happen to be on this product. Store 342 carries the most of their products and as a result has the highest revenue amongst other stores in terms of San Miguel sales (€963). A breakdown by product is shown:

	Median Unit Price (€)	Total Sales (€)	Total Volume
Product 1	0.75	16767.35	22477
Product 2	4.29	46670.55	10895
Product 3	14.99	19707.39	1261

Data Preparation

To quantify the impact of several marketing inputs, we look at each individual causal that can affect San Miguel's Sales at Pernalonga.

Causal Variable 1: TV & Radio Promotion

TV and Radio Promotion was implemented for all 3 products. The TV and radio advertisements are measured in Gross Rating Points (GRP). GRP is a standard measure in advertising, measuring advertising impact. Typically GRPs do not have a linear impact on sales and has two components:

- **Diminishing Returns:** The underlying principle for ads is that the exposure to ads creates awareness to a certain extent in the customers' minds. Beyond that, the impact of exposure to ads starts diminishing over time. Each incremental amount of GRP would have a lower effect on Sales or awareness. So, the sales generated from incremental GRP start to diminish and become constant.
- **Carry over effect or Decay Effect:** The impact of past advertisement on present sales is known as Carry over effect. A small component termed as alpha is multiplied with the past month GRP value. This component is also known as Decay effect as the impact of previous months' advertisement decays over time.

It was important to convert GRPs into a usable form for the model and so we converted the GRP values into TV and Radio reach for each product over every week. Since we have the half-life values, we calculated the decay values (ɑ values) for TV and Radio. We calculated the decay value using a half-life (h) of 4 for Radio Promotion and 8 for TV Promotion.

$$\boxed{\alpha = 1 - (0.5)\hat{}(1/h)}$$

Using this formula we got an ɑ-value of 0.15910 for Radio promotion and 0.0829 for TV promotion. We then calculated the AdStocked GRP using the ɑ-values calculated above. AdStocked GRP models natural short-term retention of media effect on consumers over time. Using the formula below we calculated the Adstocked GRP for each product. We assumed that the first time an ad was shown was the first time the product was promoted through this channel and so there is no carry over effect present.

$$\boxed{AdStock_t = \alpha GRP_t + (1-\alpha)AdStock_{t-1}}$$

Finally we converted the AdStocked GRP to Reach before inputting it into our regression model. In order to do so we used the two formulas provided; the first for TV promotions and the second for Radio Promotions.

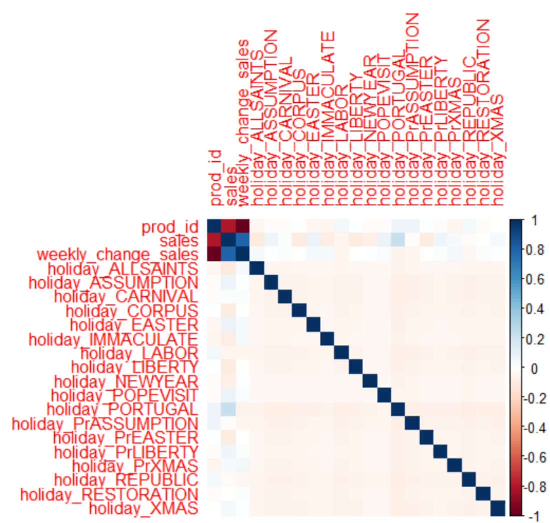
$$\boxed{Reach \;=\; 0.95\left(1 - e^{-0.020\ GRP}\right)}$$

$$\boxed{Reach \;=\; 0.90\left(1 - e^{-0.025\ GRP}\right)}$$

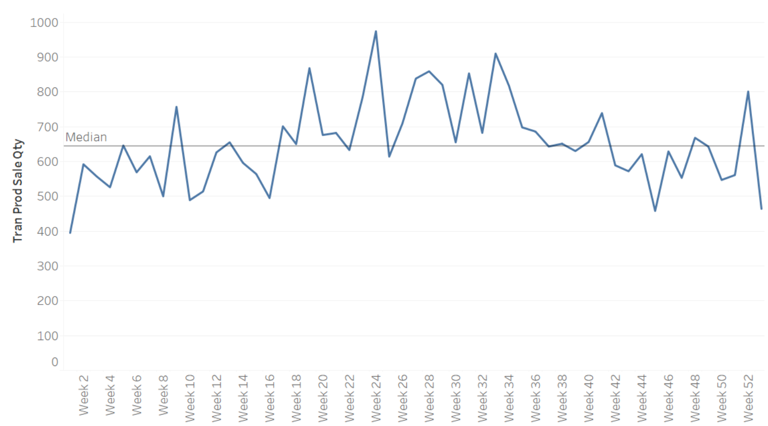
Causal Variable 2: Price & Promotion Discount

Next we wanted to account for the list price and discounted price of the products. We calculated these on a weekly basis for each product_id. For *weekly_price* we divided the total transaction sale amount for each product by the total transaction quantity by week. For the *weekly_discount* we used the average discount rate for the week.

Causal Variable 3: Seasonality & Holidays



To account for seasonality we used the Seasonality Index provided in the dataset. For holidays, we added a binary 0/1 depending on whether a holiday occurred during the week of the transaction. To do this we first tried to see which holidays had an impact (positive and negative) on sales. We looked at change in sales quantity if a holiday was present or not and calculated a correlation coefficient based off of this.



Visualizing a correlation matrix we can see which holidays have a positive/negative impact on sales and we choose to include these variables as controls in our model. From the correlation matrix we found that PopeVisit, Easter, Portugal Day, Assumption Day all have a weak positive correlation with sales. Allsaints Day, Corpus Christi, Immaculate Conception Day, New Year and PrEaster all have weak negative correlations with sales. Because of the relatively weak correlation, we decided to also look at week over week sales and see if there were any major peaks/troughs because of holidays. From this chart we found that Carnival, Portugal Day, and Assumption Day all had peaks in sales whereas PrXmas, Xmas, PrLiberty, Allsaints Day, Corpus Christi, and Immaculate Conception Day all have troughs in sales. Based on this, we decided not to include the following holidays in our dataset: *LABOR, NEW YEAR, PrASSUMPTION, REPUBLIC, RESTORATION.*

Causal Variable 4: Paid search, Web display, Email, Store display, and Flyer

Lastly, we wanted to account for the effects of other miscellaneous marketing strategies such as paid searches, web displays, email promotion, store displays, and flyers. Because each of the miscellaneous marketing strategies was not implemented for each of the 3 products, we split the data by product_id and then added the given information about the different marketing strategies to it.

Model Design

For our modeling process we decided to build a Multiplicative Model and a Logit Model to see which one yields the best insights. The multiplicative model assumes a simple implicit interaction between the causal variables which mimics reality well, i.e. in the real world there are interactions amongst the different promotions. The logit model on the other hand assumes a more complex interaction between the causal variables which is an even more realistic approach. As the logit model is bounded, we set the theoretical maximum to 10% above the maximum transaction volume so as to have positive values. We chose 10% because upon looking at the data, the variance in sales was between 10%-12% for all 3 products. The dependent variable is the sales units of each individual product and the independent variables will be the casuals we have prepared above.

After running a preliminary model we found some of the marketing efforts have negative correlations with sales which should not be the case according to our business understanding. To account for this we started by looking at the correlation matrix for each of the independent variables to account for multicollinearity and looked at box-plots to see if there were any outliers causing this. We noticed multicollinearity between TVreach and Radioreach but decided to keep both in the model to give San Miguel a better understanding of how their marketing vehicles are performing. We then looked at transformations of some of the marketing efforts to see if it could more closely match that of sales and that removed most of the negative coefficients so we proceeded with our models. The one negative coefficient was so small that it did not have a significant impact (-0.000032) on sales.

Multiplicative Model:

For the multiplicative model, we used the log of sales as the dependent variable and decided to keep some of the holidays such as *ALLSAINTS, ASSUMPTION, CARNIVAL, EASTER, IMMACULATE, PrEASTER, PrLIBERTY, XMAS, and PrXMAS* in different combinations across the three products since the holidays had a different impact on each of the three beer products. We also included all the marketing efforts - TV reach, Radio reach, Flyer, paid search, web display, and store display (only for product 2 and 3). We used a step-wise method by adding each independent variable one at a time to ascertain which variables to retain in our analysis. While testing these independent variables in a multiplicative model against log of sales, we noticed that the coefficients were mostly positive for all the marketing efforts except for some, which were extremely small in negative magnitude and thus, would not disrupt our analysis.

Logit Model:

For the logit model, we used transformed sales as the dependent variable with all the marketing efforts and the chosen holidays as the independent variables. We used different combinations of the holidays as they had different effects on the transformed sales of the three products in order to minimize any negative coefficients for the marketing efforts. Thus, the main holidays included were *ALLSAINTS, ASSUMPTION, IMMACULATE, PrLIBERTY, POPE VISIT, XMAS, PrXMAS.* The marketing efforts included TV reach, Radio reach, flyer, paid search, web display, and store display (for only product 2 and 3).

Model Diagnostics

As we built 2 models for each product, we wanted to determine which model was better in order to give the best recommendations. To do this, we performed a detailed model diagnosis looking at 5 main measures; Root Mean Squared Error (RMSE), Mean Absolute Percentage Error (MAPE), R-squared, F-Statistic, and the Durbin-Watson Statistic as there is no one-size-fits-all indicator.

MAPE is one of the most commonly used KPIs to measure forecast accuracy. MAPE divides each error individually by the demand, so it is sensitive to outliers: high errors during low-demand periods will significantly impact MAPE. A lower value of MAPE (closer to 0) is desired. From both our logit and multiplicative models for the three products, our MAPE score is lesser than 0.50 and relatively closer to 0 except for the logit model for product 3, which is 1.56. The best model in terms of MAPE for all three products is the multiplicative model, especially the multiplicative model for product 2 (which has a MAPE of 0.13).

RMSE is the square root of the mean of the square of all of the errors. RMSE is a good measure of accuracy, particularly in this case because it compares the prediction errors of our different models. Compared to MAPE, RMSE does not treat each error the same. It gives more importance to the most significant errors. That means that one big error is enough to get a very bad RMSE. From the two types of models, the multiplicative model performs better for all three products in terms of the RMSE. Multiplicative model for product 3 has the lowest RMSE value of 6.30.

R^2 is a statistical measure that represents the proportion of the variance in sales that's explained by causals we are looking at. High R^2 is usually desired but it does not mean that it provides the best fit or predictions but can be used as a rule-of-thumb. We can see from the results table below that our logit model does not have the best performance in R^2 and has negative values, which is not desirable. The multiplicative models show a better R^2 value but is still low in magnitude.

F-statistic is another measure used to test the fit of a model on the sample data. It helps us determine whether or not we should reject the null hypothesis based on our predictions. It also explains variability in terms of variability between the groups compared to variability within the group. Usually, the higher the F statistic value, the stronger the evidence is against the null hypothesis. Even though for our logit model, the values are negative, we have relatively high F statistic values for the multiplicative model. Out of all the products, product 2 performs the best in its multiplicative model in terms of F statistic.

Durbin-Watson Statistic is used to test if there is any autocorrelation which can create a bias in the coefficients. This is used for time series data. Since all of our Durbin-Watson values are relatively low (closer to 0 and 1), we do not see strong auto-correlation between our variables in any of the models. This can be indicative of the fact that we did spend considerable effort in reducing any kind of correlation from our variables during the pre-modeling process to ensure building the best possible model.

	R^2	**RMSE**	**MAPE**	**F-Statistic**	**Durbin-Watson**
Product 1 - Logit Model	-5.03	104.85	0.40	-170.27	0.18
Product 1 - Multiplicative Model	0.48	30.79	0.14	188.42	0.06

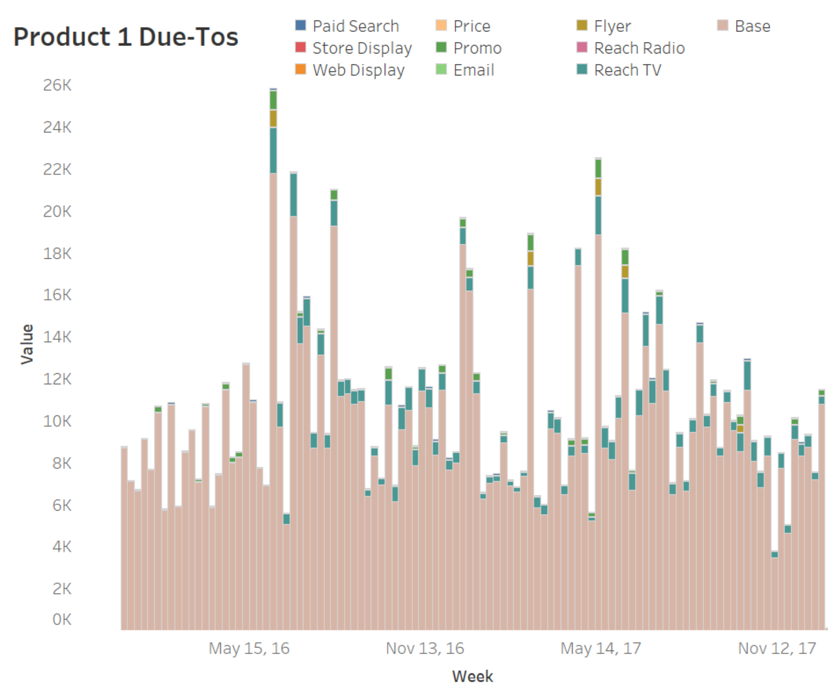
Product 2 - Logit Model	-2.18	58.51	0.39	-113.25	0.26
Product 2 - Multiplicative Model	0.74	16.87	0.13	459.65	0.08
Product 3 - Logit Model	-0.93	32.57	1.56	-16.14	0.46
Product 3 - Multiplicative Model	0.92	6.30	0.28	429.38	0.17

From this Model Diagnosis we can see that the multiplicative mode used for all the three products is a more superior model and we will be using this model moving forward; to perform model decomposition and to provide Mahou San Miguel our final recommendations.

Model Decomposition (DueTos)

In order to get the most out of this analysis, we broke down the sales into base sales and sales resulting from the various marketing campaigns (DueTos). To do this we:

1. Calculated a baseline price accounting for holidays and seasonality.
2. Calculated the DueTos for each variable in our model (price, discount, radio, TV, store display, web search, paid search, email, and flyer) by using estimated values for the given variable being equal to zero and the other variables remaining the same, allowing us to isolate the effect of each variable on sales.

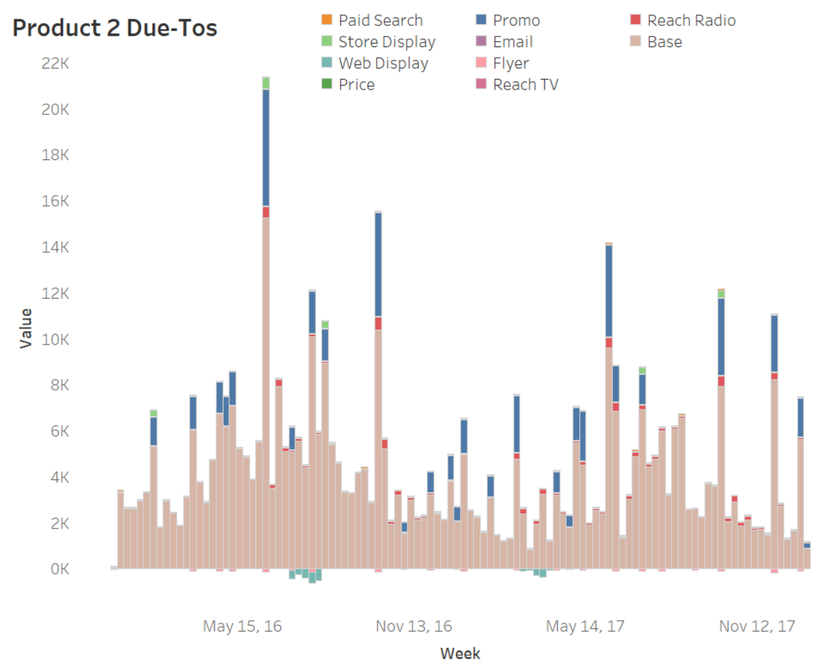


Product 1:

On visualizing the due-tos from all the marketing vehicles for Product 1 (#138936951) of San Miguel beers, we can see that reach from TV has the most impact on sales over the base amount, followed by promotion and flyers. We can see that the effect of TV is pretty consistent from early 2016 to the end of 2017. Prior to 2016, we do not see a lot of due-tos from marketing vehicles, except for a small amount from paid search.

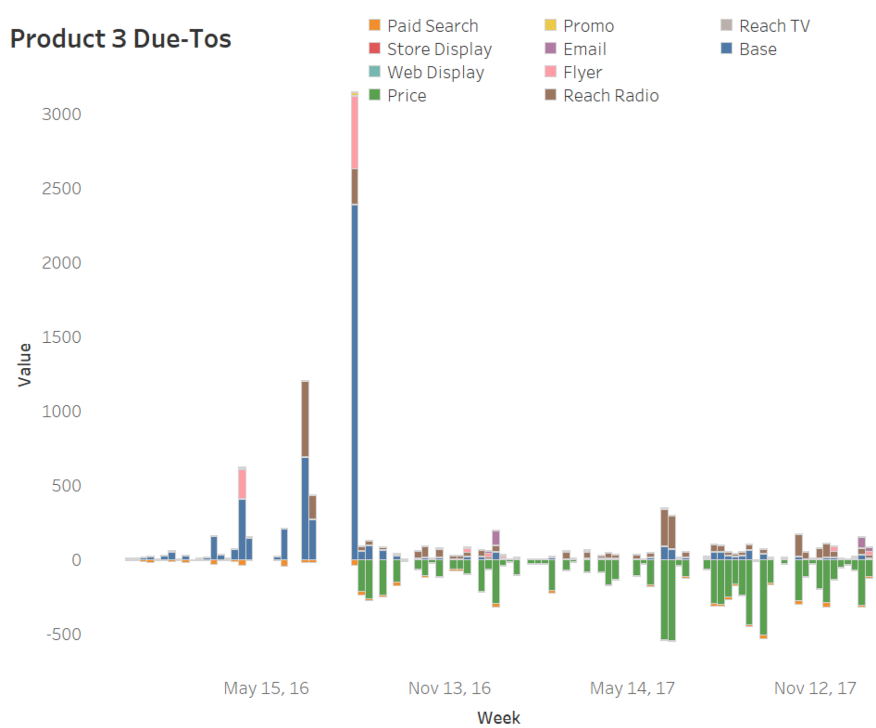
Product 2:

As we can see from the adjacent chart for the due-tos of Product 2 (#138936952), promotions contributed the largest amount to sales over the base amount of sales. As for marketing efforts; the biggest contribution came from reach acquired from Radio and Store Display. We can see there are some negative values attributed to web display, which trace back to the negative coefficients we observed in our multiplicative model. It would be helpful to see the difference in values in the future when we choose to leave the web display variable out of the multiplicative model.



Product 3:

The due-tos for Product 3 (#138936953) show that reach from Radio and Flyers had the most impact on the incremental sales of the beer for San Miguel. Additionally, we can see the large negative impact of price on the sales of this product. We also



see that the transactions are pretty sparse across the timeline. This could be due to the fact that this product has considerably less amount of transactions compared to the other two beer products. Since we can see that price has a big negative impact on sales for this product, it would be worthwhile to experiment with pricing changes in the future to improve incremental sales.

Recommendations and Next Steps

To summarize our findings, we believe the following factors have positive and negative impacts on sales for each San Miguel Product.

	Positive Impact	**Negative Impact**
Product 1	TV, Promotion, Flyers	-
Product 2	Promotion, Store Display	Web Display
Product 3	Radio, Flyers	Price

In conclusion, we can see that Marketing Mix Modeling can be a powerful tool for analyzing the effectiveness of promotional campaigns, past success, and gives great insights into planning for future campaigns. San Miguel can use the outcomes from this Marketing Mix Modeling project to further improve marketing and media plans and, ultimately, enhance the economic value of their company. Next steps for San Miguel would be to take these recommendations and use them for future marketing planning. By performing an optimization they can simulate the effect of varying each marketing tactic on future sales and determine the best combination of marketing tactics for reaching their specific goals. Additionally, a deeper dive into segment specific consumer behavior will be beneficial. Knowing what each customer segment at Pernalonga is willing to spend, their general patterns of behavior, and how they respond to ads/promotions can help lead to growth in market share and eventually, revenue.