

Team Assignment 1

Group 6

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1. Introduction

This report aims to understand the market of four chosen fast-moving consumer goods (FMCG) products in the Italian market. Two product categories, i.e. Crackers and Dry Cookies, are provided in the dataset. Of the 17 brands, four brands from the Crackers category, i.e. **Product 2**, **Product 3**, **Product 4**, and **Product 6**, are selected to be analysed further. In general, to obtain further information about the market of those products, detailed information of the demand elasticity of each product has to be extracted from the dataset. The method to capture such information will be explained in the next section. Then, the results will be discussed extensively in the following part to understand the structure and competitiveness of the market of the four brands (the market for crackers?).

Table 1: Average Price and Volume

	Average Price	Average Volume
Product 2	2.663	94527.33
Product 3	5.278	84788.64
Product 4	6.737	47015.71
Product 6	5.311	33132.16

The table above shows the average figures for each Crackers brand. By looking at those information, we assume that **Product 2** is the price leader as it has the lowest price and highest average sales volume. **Product 3** has slightly lower weekly sales despite its higher price. The product might be from a more middle segment or has a bigger package and net weight. **Product 2** and **Product 6** could be in the same segment and they are direct competitors because they have similar prices.

Product 4 could be the more premium product amongst the four brands. Those are the initial hypothesis that could be extracted by above information. The analysis that follows this section will capture more comprehensive information from the data.

2. Methodology

Our methodology will be divided into 2 parts, data transformation and regression model. Due to limited information on the dataset, we will need to perform several transformation to the data. The following part will explain the model used in the report. Linear regression models are predominantly chosen to make an inference about the relationship between price and quantity.

2.1. Data Transformation

The objective of this part is to provide the models with the most appropriate features and to separate the effect of different demand factors of each product. Prices of each brand are derived from dividing the sales value of each week by the sales volume. Since the relationship between volume and price is not known, the two variables should be converted to their log forms to adjust for models with different functional forms.

The next step is to separate the effect of promotion and observe when promotion occurred for each brand. However, **Product 2** does not have Gross Rating Point (GRP) variable which would tell the size offline advertising corresponding to the product. Another parameter is needed to see when a promotion campaign take place. The first method is to determine the week when the products are selling at discounted price. We compute the average prices (\bar{P}_i) and their standard deviation (σ_i) over 105 weeks. If the price goes below $\bar{P}_i - \sigma_i$, the **promo** variable is coded 1 during that week and 0 if otherwise. Then, the effect of GRP could also be transformed into binary variable to simplify the impact of promotion and discount on the sales volumes.

After separating all possible factors that could affect the price and volume, we need to verify the effect of promotion and discount for each product. This can be obtained by calculating the baseline sales volume and the lift. We estimate the weeks where there were advertising campaign for all products, particularly the two products without GRP data, to get the best representation of when the lift occurred.

{should explain the way we calculate baseline price & lift here?}

2.2. Regression Model

Firstly, To get the elasticity of each product and its cross elasticity against other products, we computed three models with different functional forms (Linear, Semi-Log, and Log-Log). **Volume** of the evaluated brand is the dependent variable and its **price** and promotions (**ad** and **promo**) are our first three independent variables. Then, the prices of other products and their promotion campaigns are added to the model to capture the cross-elasticity of the selected product. The process is identical for different functional forms. In general, the Full Model for **Product 2** looks like the following, but the Reduced Model are different for each product depending on the significant variables.

$$\widehat{volume_2} = a_0 + a_1price_2 + a_2ad_2 + a_3promo_2 + \sum_{i=3}^6(b_1price_i + b_2ad_i + b_3promo_i)$$

Secondly, stepwise selections are needed to omit non-significant variables from the model to get better estimation. Then, the three different functional models of each brand are compared against each other by computing their root-mean-square error (RMSE) or the difference between predicted values of **Volume** and the observed values. The model with the lowest RMSE is selected to calculate the elasticity and cross-elasticity of the product. Subsequently, the elasticity matrix can be obtained.

3. Results and Discussion

After running all model with different functional forms, different functional form models have the lowest RMSE for different products. **Product 2** and **Product 6** linear models are the most efficient as shown in **Appendix 1**. We should calculate the average price and quantity of each product over 105 weeks and compute the elasticities. The formula used to obtain these would be the following.

$$e_{ii} = a_1 \times \frac{\bar{P}_i}{\bar{Q}_i}$$

$$e_{ij} = b_1 \times \frac{\bar{P}_j}{\bar{Q}_i}$$

The Semi-Log model for **Product 3** has the lowest RMSE amongst the three in **Appendix 2**. The price elasticity formula is expressed below.

$$e_{ii} = a_1 \times \bar{P}_i$$

$$e_{ij} = b_1 \times \bar{P}_j$$

The best model for **Product 4** is the Log-Log model. Hence, the elasticities are the coefficient of the corresponding price variables. Then, the elasticity matrix and the clout and vulnerability of each product are shown below.

Table 2: Elasticity matrix of Crackers brands

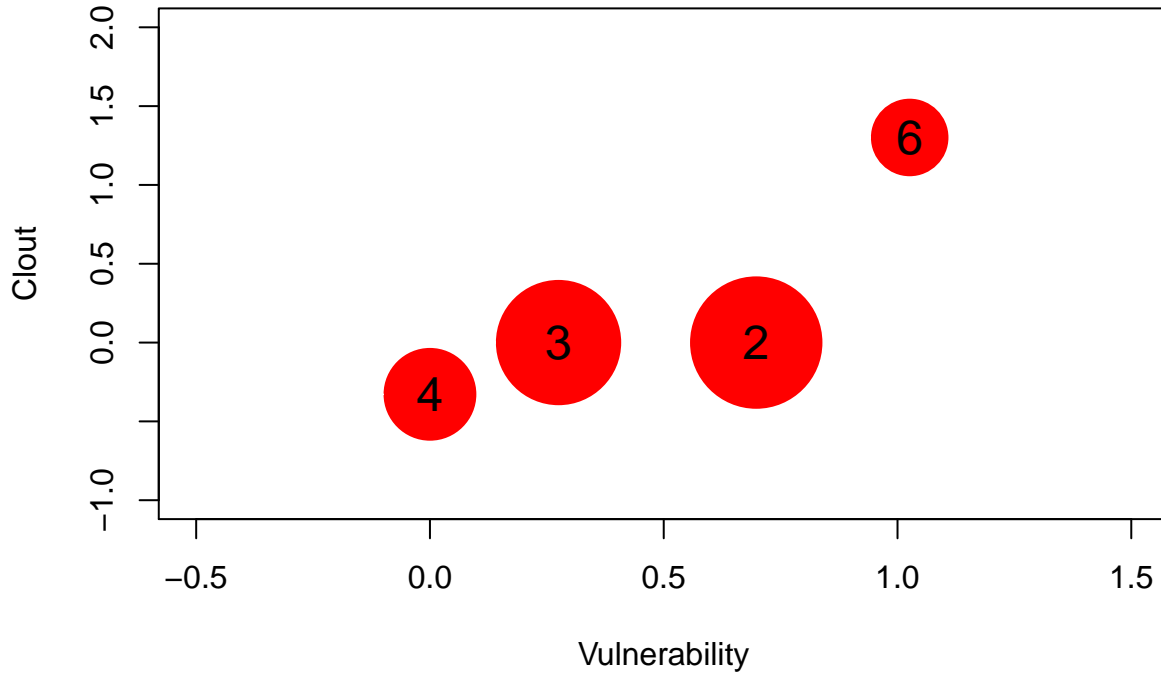
	Product 2	Product 3	Product 4	Product 6
Product 2	-1.99	0.000	-0.328	1.026
Product 3	0.00	-2.094	0.000	0.275
Product 4	0.00	0.000	-3.020	0.000
Product 6	0.00	0.000	0.000	-2.319

Table 3: Clout and Vulnerability

Product	Vulnerability	Clout
2	0.6978265	0.0000000
3	0.2750607	0.0000000
4	0.0000000	-0.3282258
6	1.0260523	1.3011130

The price elasticity of each product seems suitable for FMCG products. Their demand are elastic as expected from the market where there are many alternatives. However, the market has different products that appeals several customer segments. Using the clout and vulnerability table, we could locate the position of each brand within the market.

Crackers Market



As expected, Product 2 has the highest vulnerability because it seems to be the cheapest brand in the market and it has no power to affect other brands if it lower the price. However, if the other products lower their price, customers are more likely to switch to different brands with better quality.

4. Conclusion

Appendices