Bachelor of Science in Economics, Management and Computer Science

Predictive modeling for sales and consumption in the Fast-Moving Consumer Goods market: a regression analysis perspective

Department of Marketing

Supervisor: Jessica Jumee Kim

Rebecca Benedetti

Matr. Number: 3152342

Academic Year 2023/2024

To Professor Kim, thank you for your expertise and supervision.

A Isabella e a tutto il team Vallé, grazie per il vostro prezioso aiuto nel condurre le ricerche, oggetto della mia tesi, per l'ospitalità e per le conoscenze acquisite sul campo.

Alla mia famiglia — zii, cugini, nonni, mamma, papà e Virgi — grazie per essere sempre stati al mio fianco. In particolare, a mamma e papà, grazie per tutti i sacrifici che avete fatto per me e per l'educazione che mi avete dato. A Virgi, grazie per essere sempre stata il mio punto fermo e la mia confidente. Ai miei nonni — Nicola, Gabriella, Franco e Anna — il vostro sostegno incondizionato e la fiducia che avete sempre avuto in me mi hanno dato la forza di affrontare le difficoltà. Allo zio Andrea, grazie per avermi guidato lungo il mio percorso universitario e professionale.

A Fede, grazie per le esperienze indimenticabili che abbiamo condiviso e per il tuo sostegno costante. Grazie per aver creduto in me anche nei momenti in cui io stessa dubitavo delle mie capacità.

Ai professori del conservatorio, Premuroso e Baffero, i vostri insegnamenti nel pianoforte e nella vita hanno arricchito significativamente la mia esperienza educativa.

A tutti i miei amici, grazie per il sostegno nei momenti di bisogno e per le importanti lezioni di vita che mi avete insegnato.

To all my BEMACS classmates, thank you guys for these amazing 3 years, I hope each of you achieves your goals.

Abstract

This thesis explores the dynamic relationship between promotional activities and sales volumes in the Italian Fast-Moving Consumer Goods (FMCG) sector, with a specific focus on Vallé, a prominent player in the plant-based food market. The research leverages a comprehensive dataset provided by industry-leading Retail Data Platforms like Nielsen and Circana, to apply regression analysis and empirically assess how different marketing variables affect sales outcomes.

The core of the study revolves around the hypothesis that promotional activities positively influence sales volumes. This was examined against a backdrop of fluctuating market conditions, product pricing strategies, and the overall competitive landscape.

Empirical findings from the thesis reveal a significant positive relationship between promotional activities and sales volumes. The analysis demonstrates complex interactions between promotional percentages, market trends, and pricing, highlighting also the critical role of market share and seasonality in influencing sales outcomes.

The results emphasize that targeted promotional strategies, like discounts and limited-time offers, effectively increase FMCG sales. It also suggests that companies should tailor pricing strategies to consumer sensitivity and product positioning for better market segmentation.

The thesis proposes future research to examine the long-term effects of promotional strategies on brand loyalty and consumer perception, and to analyze the varying impacts of different promotional types. It also suggests expanding research to include more product categories, which could enhance understanding of effective marketing strategies across diverse market segments.

Index of Contents

1. **Introduction**

1.1 Background and context

The fast-moving consumer goods market is characterized by high consumer demand, rapid turnover of products and competition among brands. In this dynamic landscape, companies continuously seek innovative strategies to enhance their sales performance and maintain their market position. One such strategy is the employment of promotions, which play an important role in driving sales and influencing consumer behavior.

According to NIQ's Retail Spend Barometer, which combines data from NIQ (Nielsen IQ) and GfK (Gesellschaft für Konsumforaschung) to measure the turnover of FMCG purchased in stores in Italy, in 2023 the FMCG sector experienced significant revenue growth, surpassing €134 billion, a 7.9% increase from the previous year. Among the various categories, food products saw the most substantial growth, with an 8.9% increase and a turnover of 82 billion euros.

Within the FMCG market the plant-based food category is experiencing significant growth, driven by changing consumer preferences towards more sustainable and healthier diets. In 2023, the Italian plant-based food market, which is the third largest in Europe, reached a value of approximately 588 million euros.

Vallé, an Italian food company specializing in plant-based products, operates within this expanding market segment. The company made its debut in the market in 1975 with a margarine, a vegetable fat often used as a substitute for the more common butter. Launched in Milan, Vallé margarine quickly gained popularity thanks to its delicious taste and versatility in the kitchen. Offering a lighter and healthier option compared to traditional butter, Vallé has shown itself to be at the forefront in offering products that meet the modern needs of health- conscious consumers. Over the years, the company has continued to expand its range of products, including cake bases in 2001, becoming a reliable choice for home pastry lovers. Recently it once again demonstrated its leadership in food innovation with the launch of a vegetable mascarpone, addressing the growing demand for plant-based and sustainable alternatives. What sets Vallé apart is its commitment to the quality and health of consumers. All products are made without the use of hydrogenated facts, in accordance with the Self-Discipline Code.

Vallé is a key player in the Italian margarine market, which stands as its most significant arena of operation and direct competition with butter.
In 2022 and 2023, the margarine market in Italy saw a modest reduction in volume from 6,785 tons to 6,603 tons. Despite this decline, the market value increased from €31,034,302 to €34,167,919. This rise in market value, despite the decline in volume, indicates an increase in the unit price of margarine or a shift towards premium products that fetch higher prices. Vallé has successfully expanded its footprint in this sector, with its market share by volume growing from 43.4% in 2022 to 45.4% in 2023. This growth suggests that Vallé not only managed to navigate through the market's overall shrinkage but also likely gained ground at the expense of smaller competitors.
Meanwhile, the butter market also experienced growth during the same period, with sales values escalating from €465,939,435 to €485,437,491 and volumes rising from 43,074 to 43,581 tons. These figures reflect a strong consumer demand for butter, positioning it as a formidable rival to

margarine, despite their differing nutritional profiles and pricing structures (Nielsen IQ).

1.2 Objectives of the study

Promotional activities play a pivotal role in the FMCG sector, serving as essential drivers for brand visibility, consumer engagement, and ultimately, sales growth. For a company like Vallé, with its unique positioning in the plant-based segment, promotions not only serve as sales tactics, but also as educational tools aimed at informing potential consumers about the benefits and qualities of plant-based products. The challenge for Vallé lies in effectively leveraging these promotions to drive both short-term sales and long-term brand loyalty in a competitive market.

In our research we will focus on the effect of the independent variable (IV) Promo Percentage on the dependent variable (DV) Volume Sales. Specifically, we aim to assess whether fluctuations in the promo percentage exert a discernible influence on volume sales, and if so, whether these effects manifest as increases or decreases in sales volume. The main ideas are discussed, the hypotheses are explicitly put forth, and the methodology is explained in depth in the sections that follow.

1.3 Significance of sales forecasting and forecasting methods

The importance of precise sales forecasting in the fast-moving consumer goods market cannot be overstated. In this dynamic industry landscape characterized by rapid product turnover and evolving consumer trends, accurate sales forecasts are essential for strategic decision-making and operational efficiency.

One key aspect where accurate sales forecasting proves invaluable is in inventory management. FMCG products, known for their short shelf lives and high turnover rates, demand meticulous inventory control. By accurately predicting sales, Vallé can effectively manage its inventory levels, minimizing the risk of overstocking and reducing instances of spoilage and waste. This not only translates to cost savings but also aligns with Vallé's commitment to sustainability by minimizing its environmental footprint.

Moreover, reliable sales forecasts play a pivotal role in nurturing relationships with retail partners. In fact, retailers value suppliers who can provide accurate sales forecasts as it aids them in their own stock management efforts.

Precise sales forecasting also informs marketing strategies and promotional activities, thus allowing Vallé to allocate marketing resources efficiently, targeting promotions when and where they will be most effective. The ability to forecast sales accurately allows for nimble responses to market changes and competitor actions, thus conferring competitive advantage and achieving market share growth.

Additionally, in the context of new product introductions, sales forecasting aids in predicting the market reception and potential sales volumes, guiding product launch strategies and investment decisions.

Against this backdrop, the adoption of sophisticated forecasting methods assumes critical importance. The choice of the method often depends on the data availability, the complexity of the market dynamics, and the specific product characteristics.

Qualitative forecasting methods, encompassing expert judgment and market research, play a crucial role, particularly in scenarios where historical data may be sparse or nonexistent, such as with new product launches.

Conversely, quantitative methods like time series analysis offer valuable tools for forecasting sales based on historical data patterns. By analyzing historical sales data, Vallé can gain insights into recurring patterns and leverage this information to project future sales trajectories with greater precision.

Causal models, exemplified by regression analysis, offer another forecasting approach for sales forecasting. By exploring the causal relationships between sales and various influencing factors such as pricing strategies, promotional activities and competitor actions, Vallé can discern the drivers of sales performance and make informed decisions to optimize its marketing and sales strategies.

Furthermore, market tests represent a practical avenue for gathering direct feedback on consumer response to new products or marketing initiatives.

Given the database available for analysis, regression analysis emerges as the most suitable method for conducting promotion analysis for Vallé's plant-based products, as it offers a robust framework for exploring relationships between factors like promotional activities and sales volume. With regression analysis, the company can quantify the effects of promotions, control for confounding variables, and assess statistical significance.

1.4 Scope and limitations

This study delves specifically into the influence of promotions on sales volume within the FMCG market, using Vallé Italia as the primary case study company. While the findings hold potential relevance for other FMCG companies, it's crucial to acknowledge certain limitations inherent in the study.

Firstly, potential constraints related to data availability may impact the depth and breadth of the analysis. Depending on the scope of the dataset accessible, certain nuances or variables relevant to promotions and sales volume may not be fully captured.

Secondly, while the insights derived from this research may offer valuable implications for industry practitioners, the generalizability of the findings to all FMCG companies may be limited. Variations in market dynamics, consumer behavior, and competitive landscapes across different product categories could affect the applicability of the study's conclusions.

Additionally, the dynamic nature of market conditions should be taken into account. The conclusions drawn from this study may reflect a specific snapshot in time and may require periodic reassessment to remain relevant.

2. **Literature review**

2.1 Conceptual framework

The dataset provides a comprehensive foundation for assessing sales performance in the FMCG sector, with a focus on Vallé's plant-based product line. Each data point contains essential retail indicators that offer invaluable insights into Vallé's market dynamics and performance metrics.

The identifiers item and item ID allow for a disaggregated analysis at the product level, making it easier to look closely at each product's performance within Vallé's wide range of offerings.

Market trend and company trend indicators respectively reflect the general direction of the product category and Vallé’s own sales trajectory. These indicators provide insight into the company’s relative performance and strategic positioning.

Volume sales are the main dependent variable in regression analysis and provide an evaluation of Vallé's overall product success across different periods.

Additional measures that help to explain Vallé's brand visibility, sales efficiency, market presence and competitive position include the average number of references, rotations, weighted distribution, and market share. These indicators highlight the effectiveness of Vallé’s distribution plans and placement in the marketplace.

Variables like price and promotion percentage are important levers that affect customer behavior and sales results. Price elasticity of demand and the effect of promotional activities on sales volume may be evaluated by analyzing these variables, which offers useful information for pricing and marketing strategies.

Including seasonality as a variable to the study helps taking into consideration seasonal trends.

2.2 Theoretical framework

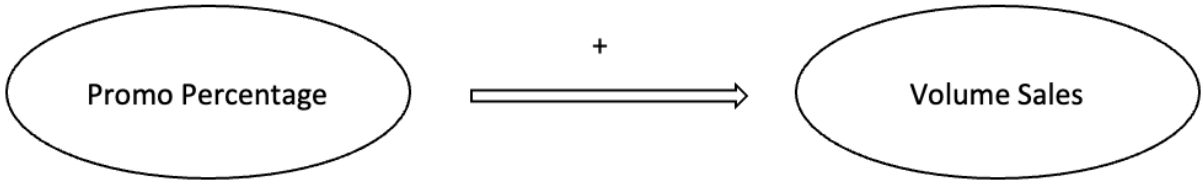
a) Promotional analysis and linked theories

By taking into consideration researches made in the past, I found out that many questions related to promotional analysis had already been addressed.

Numerous academic research have analyzed the relationship between promotions and volume sales. The comprehensive study by Ali and Muhammad (2021) within the FMCG industry elucidates a discernible correlation between the utilization of sales promotion techniques, and a marked increment in consumer buying behavior. This correlation underscores the efficacy of sales promotions as a driver for enhancing product uptake and revenue. Further substantiation comes from a separate analysis on the influence of sales promotions on category sales within large retail establishments, which confirms that promotion policy variables significantly impact the average level of category sales (Ifeanyi-Obi, Lemchi, & Isife, 2008). These findings suggest that strategic promotional activities can indeed act as a driving force for increasing sales volume across diverse commercial contexts.

Based on what written above, we would like to test the following theory:

- H0: There is a positive relationship between promotional percentage and volume sales of Vallé’s plant-based product line.



b) Seasonality theory
Seasonality theory suggests that certain patterns or trends repeat themselves at regular intervals within specific time frames, influenced by factors like weather, holidays, or cultural events. These recurring patterns can significantly influence consumer behavior and market demand throughout the year. This view is susteained by GlobalData's report "Global Executives Survey: Impact of Seasonality in FMCG industry". (GlobalData, 2017).

During holiday seasons or peak shopping periods, retailers frequently increase promotional activities to leverage heightened consumer spending. However, it's essential to recognize that the effectiveness of promotions during these times might be obscured by the inherent rise in sales due to seasonal factors, rather than solely credited to the promotional endeavors themselves.

This theory can be summarized saying that festive seasons have a positive impact on volume sales.

c) Resource-based view theory and brand loyalty theory
According to the Resource-based view theory, firms with more resources are positioned strategically to engage in more extensive promotional activities. Businesses with larger market shares typically have access to

large amounts of capital and established brand awareness. Taking advantage of these benefits, they strategically spend a large amount of money on marketing initiatives in an effort to maintain or increase their market share (Valaei et al, 2021).

Brand loyalty theory highlights the significant influence that customer loyalty has on market dynamics. Companies with larger market shares generally have higher levels of brand loyalty from their customers (Moisescu, 2012). This loyalty results in repeat purchases and a larger share of total market sales volume.

These theories can be summarized saying that a higher market share has a positive impact volume sales.

Based the seasonality theory (b), and the resource-based view theory and brand loyalty theory (c), we can identify some confounders that might influence the result and help us explain the final effect on the dependent variable.

c) Price perception theory

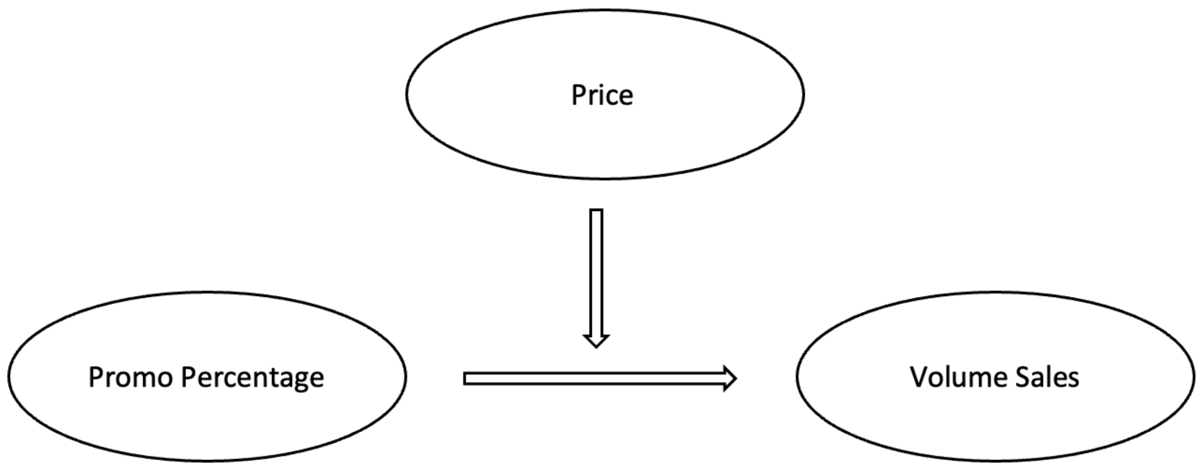
The Price perception theory delves into how consumers interpret and react to prices. This theory asserts that consumers' perceptions of prices are not solely based on objective monetary values but are influenced by various factors.

Key concepts include subjective value, reference prices, perceived quality, psychological pricing, perceived savings, price-quality inference, temporal factors, and social influence. These factors influence consumers' assessments of price fairness, product quality, and perceived value, ultimately impacting their purchasing decisions (Ridgway, 1993).

For instance, the effectiveness of promotional discounts may vary depending on the level of the base price. Higher-priced items may require larger discounts to attract consumers, while lower-priced items may be more sensitive to smaller discounts.

We can thus formulate a new hypothesis:

- H1: For a given promotional discount, the higher-priced the item, the greater the decrease in volume sales.



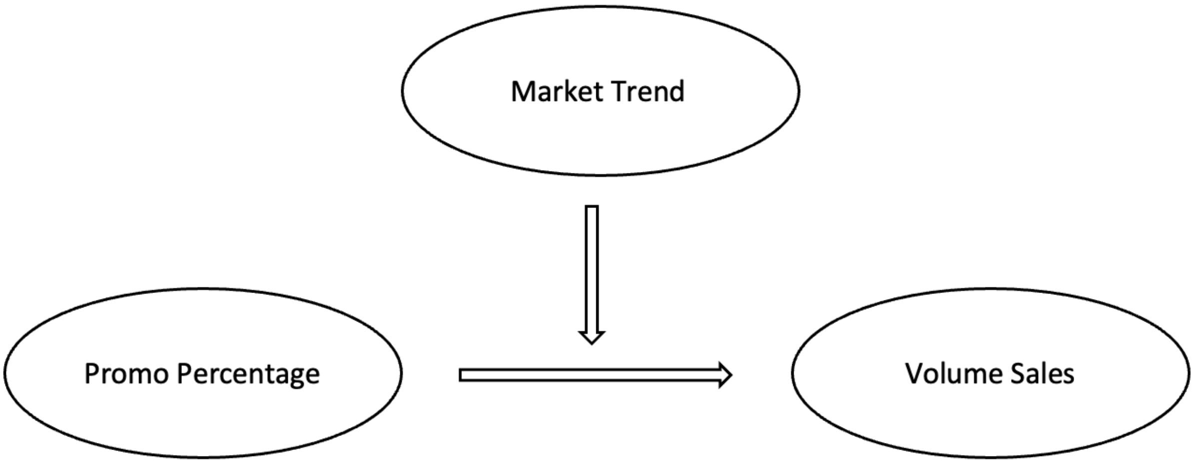
d) Resource allocation theory

Resource Allocation Theory, also known as Resource Dependence Theory, is a fundamental concept in organizational theory and strategic management. It emphasizes how organizations rely on external resources to achieve their objectives and maintain their operations. The theory suggests that organizations are influenced by their external environment, including market conditions, regulatory frameworks, and relationships with other entities (Trihatmoko & Novela, 2022)

Positive market trends, signaling economic growth or heightened consumer demand, offer organizations more resources, prompting increased promotional investments.
By aligning promotional strategies with prevailing market conditions, organizations optimize resource allocation, maximizing sales outcomes.

Therefore the last hypothesis is:

- H2: The more positive the market trend, the greater the impact of promotions on sales.



3. **Methodology**

3.1 Overview of internship experience

This study is informed and enriched by a comprehensive internship experience at Vallé Italia. The internship was an integral part of the learning journey, providing practical insights into the FMCG sector and hands-on experience with data analysis in a real-world context.

A key aspect of the internship involved engaging with Retail Data Platforms like Nielsen and Circana, essential tools for acquiring market insights. The focus was on comprehending FMCG market dynamics, especially in the plant-based niche, through in-depth trend analysis and examination of the competitive landscape. Additionally, the internship promoted the development of skilled analytical abilities and tool competence by allowing the application of theoretical knowledge to practical problem-solving settings.

The internship also offered a chance to work across different departments, from marketing to supply chain management, understanding how each function contributes to the company's overall success and how data ties these functions together.

Additionally, participating in strategy sessions, where insights from data analysis were used to shape marketing and sales strategies, was an invaluable experience.

3.2 Data collection methods

Focusing on Nielsen and Circana, these platforms offer a large amount of data crucial for understanding consumer behavior, market trends, and the competitive landscape. Their importance in the context of this research lies in their comprehensive coverage of sales data, promotional activities, and market shares, which are essential for conducting promotional analysis using linear regression.

Both Nielsen and Circana are renowned for their extensive databases that assemble retail sales data across various channels, ensuring data richness and reliability. This solid foundation provides unparalleled insights into market dynamics and consumer preferences within the FMCG sector.

Utilizing data available on these platforms enables the identification of short-term fluctuations and long-term trends in sales, consumer preferences, and market dynamics. This trend analysis serves as a basis for forecasting future sales and strategic planning.

Moreover, these platforms offer sophisticated analytical tools and customizable reporting features. Leveraging these tools for ad-hoc analysis, custom report generation, and visual data presentations during the internship facilitated the derivation of actionable insights from complex datasets.

By leveraging Nielsen and Circana, the research benefits from authoritative sources of retail data in the FMCG industry. The insights gained from these platforms are central to the empirical model developed in this thesis, underscoring the importance of leveraging industry-standard tools for market analysis and sales forecasting.

4. **Empirical model and data**

4.1 Empirical models

As previously described with H0, the simplest regression is:

$$volume\_sales_i = \beta_0 + \beta_1 promo\_percentage_i + e_i$$

Proceeding in the study, we addressed the effect that the seasonality theory, and the resource-based view theory and brand loyalty theory have on the final measure of the volume sales, and these variables will be considered as confounders in the model.

Hence, we proceed with a regression including the variables "seasonality_index" and "market_share".

Here is the model:

$$volume\_sales_i = \beta_0 + \beta_1 promo\_percentage_i + \beta_2 seasonality\_index_i + \beta_3 market\_share_i + e_i$$

In H1, we studied the addition of another interaction term, which is composed of the variables "price" and "promo_percentage". To implement this, the variables have to be encoded through an interaction term. Since there is a moderator in the model, everything is centered to make things easier.

Here is the model:

$$volume\_sales_i = \beta_0 + \beta_1 promo\_percentage_i + \beta_2 seasonality\_index_i + \beta_3 market\_share_i + \beta_4 price_i + \beta_5 (price_i * promo\_percentage_i) + e_i$$

Furthermore, as previously discussed in the theoretical framework for H2, we decided to analyze the joint effect of the variables "market_trend" and "promo-percentage" to understand how the final feedback of a customer changes when their expectations are met or not.

And here is the model:

$$volume\_sales_i = \beta_0 + \beta_1 promo\_percentage_i + \beta_2 seasonality\_index_i + \beta_3 market\_share_i + \beta_4 price_i + \beta_5 market\_trend_i + \beta_6 (price_i * promo\_percentage_i) + \beta_7 (market\_trend_i * promo\_percentage_i) + e_i$$

After having translated the theories into empirical models, it is crucial to account for unobservable factors. These could lead to bias in the output of the regression, producing incorrect results. In the panel dataset, we are dealing with a variety of products. Products present differences when it comes to the quality, design and target audience. All these may act as possible unobservable confounders.
The most reasonable solution to this problem would be to get rid of between-product differences (between variation) and focus on within product differences. We do this by introducing the firm fixed-effect into the model.

Given that we have panel data with multiple observations over time for various products, we can also include time-fixed effects in our regression model. Even though the data in our dataset is collected weekly, we decided to analyze it quarterly. This decision helps to reduce noise from short-term fluctuations, providing a clearer view of underlying trends. Additionaly, quarterly analysis captures seasonal patterns more effectively, aligns with standard business cycles, and simplifies the data management process. It also enhances the statistical robustness of our analysis by increasing observations per time point.

5. **Data analysis and results**

5.1 Descriptive statistics

We start the analysis by providing descriptive statistics.
Firstly, we run the command summarize on all variables which are not categorical or dummies, to familiarize with the dataset and to have a general overview of the data.

Descriptive Statistics

Variable	Obs	Mean	Std. Dev.	Min	Max
item id	815	2017859.4	3.139	2017856	2017865
market trend	815	130311.56	36154.04	82687.208	284780.7
firm trend	815	57497.61	21225.696	32291.731	148089.08
volume sales	815	11476.165	9670.347	101.561	71436.964
avg references	815	1	0	1	1.005
weighted distribut~n	815	41.52	14.809	3.864	64.406
market share	815	8.689	5.936	.069	27.538
base price	815	6.773	1.239	4.272	8.787
promo percentage	815	22.388	15.374	0	86.79
seasonality index	815	100	36.916	56.162	257.557

The summary table provides a concise overview of key sales data characteristics across several variables for 815 observations. Notably, 'item_id' exhibits very little variation, which implies a limited range of items under review. In contrast, 'market_trend' and 'volume_sales' show high variability, highlighting significant fluctuations in market conditions and sales volumes respectively.

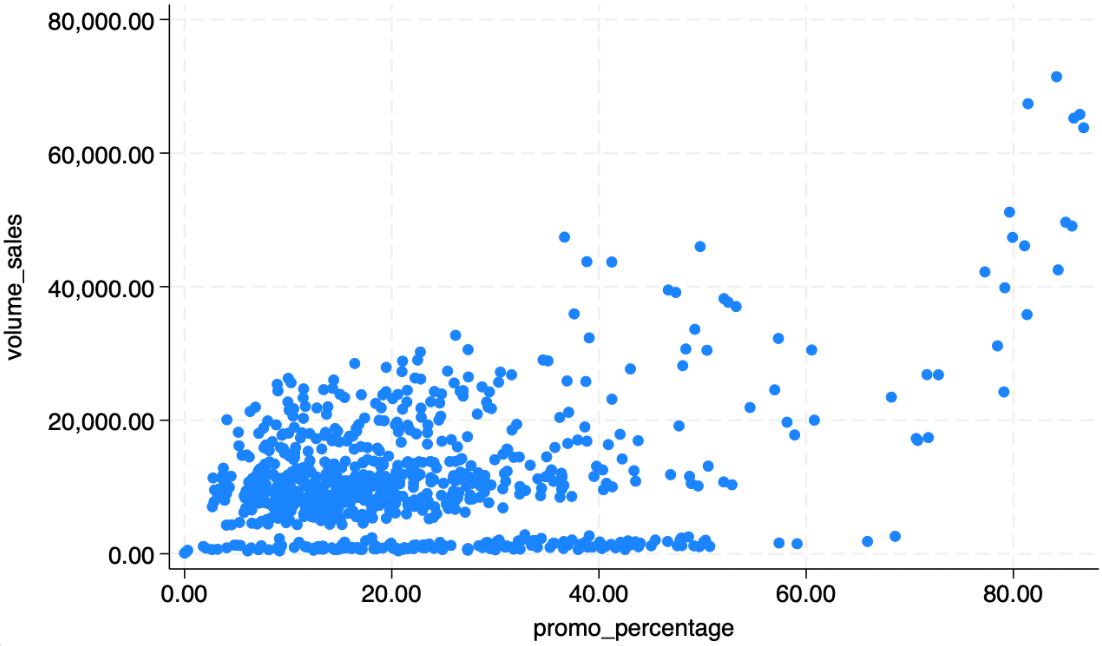
Then we explore the correlation between variables for exploratory purposes as we cannot infer if a variable is significant or not based on its correlation with the dependent variable.

Matrix of correlations

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
(1) volume_sales	1.000								
(2) promo_percentage	0.417	1.000							
(3) market_trend	0.421	0.324	1.000						
(4) firm_trend	0.438	0.333	0.963	1.000					
(5) avg_references	-0.008	0.004	-0.020	-0.004	1.000				
(6) weighted_distr~n	0.490	-0.176	0.124	0.118	0.063	1.000			
(7) market_share	0.889	0.222	0.072	0.102	0.001	0.581	1.000		
(8) base_price	-0.481	-0.222	-0.033	0.038	0.068	-0.013	-0.535	1.000	
(9) seasonality_in~x	0.438	0.333	0.963	1.000	-0.004	0.118	0.102	0.038	1.000

As expected, there is a significant positive correlation between volume sales and promotional activities, indicating that increased promotions tend to drive higher sales volumes. Additionally, volume sales exhibit a strong positive relationship with market share, market trend and seasonality. Conversely, volume sales are negatively correlated with base price.

Before diving into the regression analysis, it's essential to visually assess the relationship between our chosen independent and dependent variables. This is why, by drawing a scatter plot, we further explore the variable “promo_percentage” and its relationship with “volume_sales”.



The scatter plot depicting the relationship between promotional activities and sales volumes reveals a trend where increases in promotional percentages generally correlate with higher sales volumes. Most data points are concentrated at lower promotion levels, with sales volumes predominantly under 20,000 units, suggesting that minimal promotions are common practice. However, the plot also shows that as promotional activities intensify, the variability in sales volumes becomes more pronounced. This indicates that while high promotional efforts can significantly boost sales, their effectiveness varies, hinting at the influence of other factors in the sales process.

5.2 Results and interpretations

- H0

We run the basic regression between the main independent variable, “promo_percentage”, and the dependent variable “volume_sales”, which we analyzed in the model (Model 1):

$$volume\_sales_i = \beta_0 + \beta_1 promo\_percentage_i + e_i$$

Subsequently, we try to run a regression introducing all the confounders previously discussed (Model 2):

$$volume\_sales_i = \beta_0 + \beta_1 promo\_percentage_i + \beta_2 seasonality\_index_i + \beta_3 market\_share_i + e_i$$

Here we run the regressions.

VARIABLES	(1) volume_sales	(2) volume_sales
promo_percentage	262.2***	81.79***
	(20.05)	(6.485)
seasonality_index		81.15***
		(2.647)
market_share		1,350***
		(15.92)
Constant	5,607***	-10,197***
	(544.5)	(289.7)
Observations	815	815
R-squared	0.174	0.926

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

We observe that in Model 1 the “promo_percentage” variable is significant and has a positive coefficient, and we see that one additional unit of standardization is associated with an increase 262.2 units in volume sales. So in this regression, performed in absence of confounders and moderators, our basic hypothesis H0, in which we stated that there is a positive relationship between promotional percentage and volume sales of Vallé's plant-based product line, is not rejected.

In Model 2 we observe that one additional unit in "seasonality_index" is associated with 81.1 additional units in "volume_sales". One additional unit of "market_share" is associated with 1350 additional units of "volume_sales". Additionally, both variables are significant in the regression, as we expected from the theory in the previous section.
We see that an additional unit of "promo_percentage" still meets our assumptions as it is associated with an increase of 81.8 units in volume sales.

- H1

Let's see the model (Model 3) where we analyze the effect of moderators on our variables by introducing an interaction term, and we study the interaction between "promo_percentage" and "base_price":

$$volume\_sales_i = \beta_0 + \beta_1 promo\_percentage_i + \beta_2 seasonality\_index_i + \beta_3 market\_share_i + \beta_4 price_i + \beta_5 (price_i * promo\_percentage_i) + e_i$$

- H2

As another interaction term, we analyze the interaction between "promo_percentage" and "market_trend" as well, including all confounders (Model 4):

$$volume\_sales_i = \beta_0 + \beta_1 promo\_percentage_i + \beta_2 seasonality\_index_i + \beta_3 market\_share_i + \beta_4 price_i + \beta_5 market\_trend_i + \beta_6 (price_i * promo\_percentage_i) + \beta_7 (market\_trend_i * promo\_percentage_i) + e_i$$

We run the regressions.

VARIABLES	(3) volume_sales	(4) volume_sales
c_market_trend		0.0931***
		(0.00698)
c_promo_percentage	57.33***	21.19***
	(6.930)	(5.093)
c.c_market_trend#c.c_promo_percentage		0.00229***
		(8.99e-05)
c_base_price	-284.3***	-19.38
	(86.83)	(65.91)
o.c_promo_percentage		-
c.c_base_price#c.c_promo_percentage	-34.37***	-13.00***
	(4.464)	(3.317)
c_seasonality_index	79.69***	-16.65**
	(2.603)	(6.974)
c_market_share	1,290***	1,257***
	(18.52)	(13.90)
Constant	11,331***	11,009***
	(90.62)	(65.15)
Observations	815	815
R-squared	0.932	0.966

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

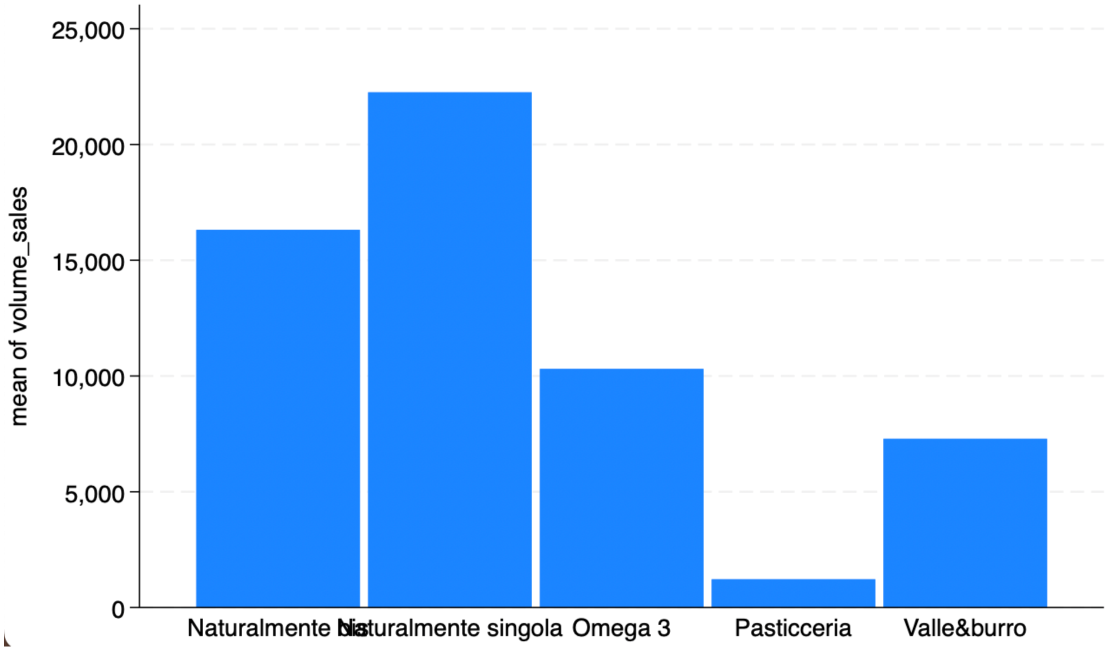
First, we analyze Model 3. The addition of the interaction term implies that the effect of promo percentage on volume sales isn't constant but changes depending on the level of the base price. So a unit increase in “base_price” results in a decrease of 34.4 units in the effect of “promo_percentage” on “volume_sales”. If “base_value” is at its mean value (i.e. “c_base_value” is at 0), the average effect of “promo_percentage” on “volume_sales” is simply the coefficient of “promo_percentage” (57.3). The model is statistically significant, meaning that the F-statistic is significant with a p-value near 0.

Looking at Model 4, we observe that the coefficient for the centered value of promo percentage, after the introduction of both interaction terms, decreases. So we can say that now one additional unit of “promo_percentage” (centered value) is associated with 21.2 units increase of “volume_sales”, and the variable is significant.

The impact of “promo_percentage” on “volume_sales” is influenced by both “market_trend” and “base_price”. As the levels of these moderators change, so does the relationship between “promo_percentage” and “volume_sales”. Specifically, for every unit increase in “base_price”, the influence of “promo_percentage” on “volume_sales” decreases by 13.0 units. Interestingly, a unit rise in “market_trend” results in a very small increase of 0.002 units in the effect of “promo_percentage” on “volume_sales”. This means “base_price” is an important moderator between “promo_percentage” and “volume_sales”, while “market_trend” has a smaller impact.
We also note that the variable “base_price” becomes non significant in the regression and that the seasonality effect flips to negative.
Additionaly, we can observe that the model is significant as the F-statistic p-value is near 0. The model explains 96.6% of the variance in “volume_sales”, which is slightly better as there is an increase from the previous model that had an R-squared of 93.2%. This suggests that the inclusion of the additional terms provided some added explanatory power.

- Fixed-Effects model

Since the volume sales vary across the products (as we can see in the graph below), we decided to introduce a fixed effects model (Model 5), as previously mentioned.



-Time-Fixed-Effects model

Given that we have panel data with weekly observations over time (starting from February 15, 2021 to March 25, 2024) for various products, we can can include time-fixed effects in our regression model (Model 6). We decided to do a quarterly analysis.

We run the regression including fixed-effects and time-fixed-effects.

VARIABLES	(4) volume_sales	(5) volume_sales	(6) volume_sales
c_market_trend	0.0931***	0.0935***	0.0876***
	(0.00698)	(0.00782)	(0.00861)
c_promo_percentage	21.19***	26.88***	26.05***
	(5.093)	(5.855)	(5.935)
c.c_market_trend#c.c_promo_percentage	0.00229***	0.00235***	0.00238***
	(8.99e-05)	(9.61e-05)	(9.78e-05)
c_base_price	-19.38	94.60	41.08
	(65.91)	(127.0)	(131.2)
o.c_promo_percentage	-	-	-
c.c_base_price#c.c_promo_percentage	-13.00***	-12.89***	-13.82***
	(3.317)	(3.691)	(3.737)
c_seasonality_index	-16.65**	-17.46**	-13.54*
	(6.974)	(7.746)	(8.193)
c_market_share	1,257***	1,199***	1,188***
	(13.90)	(44.74)	(45.51)
2.quarters			-272.9
			(187.1)
3.quarters			-397.4*
			(204.5)
4.quarters			-144.2
			(174.9)
Constant	11,009***	11,000***	11,186***
	(65.15)	(66.19)	(122.8)
Observations	815	815	815
R-squared	0.966	0.923	0.923
Number of item_id		5	5

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

In Model 5, the F-statistic is still near to 0, meaning that the individual effects of the regressors are jointly significant.
In the model without fixed effects (Model 4), promotional percentage significantly enhanced sales volume. Similarly, the interaction term with "market_trend" has a positive impact on sales, while the influence of the interaction term with "base price" was negative, indicating that higher prices typically suppress sales volumes.
In the fixed-effects model (Model 5), both market trends and promotional activities retain significant positive impacts on sales volumes, with promotions showing even greater influence here than in the non-fixed model. The increase in the effect that "promo_percentage" has on "volume_sales" suggests that controlling for within-product variation reveals a stronger relationship between our dependent and main independent variable.

Interestingly, the base price effect flips to positive, suggesting that higher prices do not necessarily deter sales when item-specific characteristics are controlled, pointing to a potential premiumization effect where higher prices might indicate higher value to consumers.
Seasonality continues to show a consistent negative effect, while market share remains a robust positive driver of sales volumes.
The model captures 92.3% of the variance in sales volumes within each item across time, according to the Within R-squared of 0.9227. The Overall R-squared of 0.9653 indicates that 96.53% of the entire variation in the data is accounted for by the model, while the Between R-squared of 0.9997 shows almost perfect explanation of the variance between different items. These values collectively demonstrate that the model is highly effective in capturing the dynamics and effects influencing sales volumes both within and between items.

We observe that in Model 6 promotional activities still significantly boost sales volumes. Compared to the fixed-effect model, in the time-fixed-effect model, the effect that "promo_percentage" has on "volume_sales" is a little lower. In both models, the interaction terms are significant, with the one with the variable "market_trend" increasing sales, and the one with "base_price" having a negative impact. Interestingly, compared to the other model, the seasonality index becomes non-significant. The coefficients for quarters are not significant in the time-fixed-effect model, with Q2 and Q3 showing strong negative values. This suggests that quarterly variations do not have a significant standalone impact on sales when other factors are controlled. Both models exhibit high R-squared values.

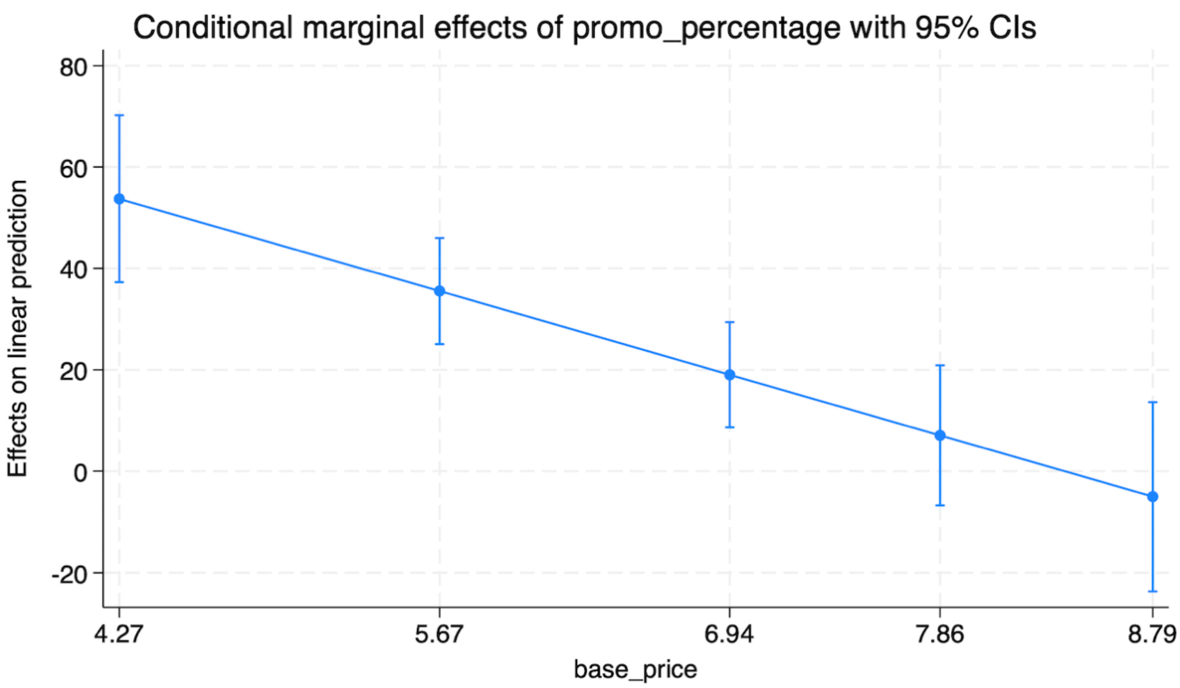
-Margin plots

Finally, we analyze the margins plots, whose aim is to investigate the extent of the effect of our moderator variables across various levels (minimum value, 25th percentile, 50th percentile, 75th percentile and maximum value).

Let's analyze the margins plot for "base_price" first.

Conditional marginal effects   Number of obs = 815
Model VCE: OLS
Expression: Linear prediction, predict()
dy/dx wrt: promo_percentage

		Delta-method				
	dy/dx	std. err.	t	P>t	[95% conf.	interval]
promo_percentage						
_at						
1	53.727	8.387	6.410	0.000	37.263	70.191
2	35.531	5.340	6.650	0.000	25.048	46.013
3	19.024	5.280	3.600	0.000	8.660	29.387
4	7.066	7.041	1.000	0.316	-6.754	20.886
5	-5.022	9.509	-0.530	0.598	-23.688	13.644

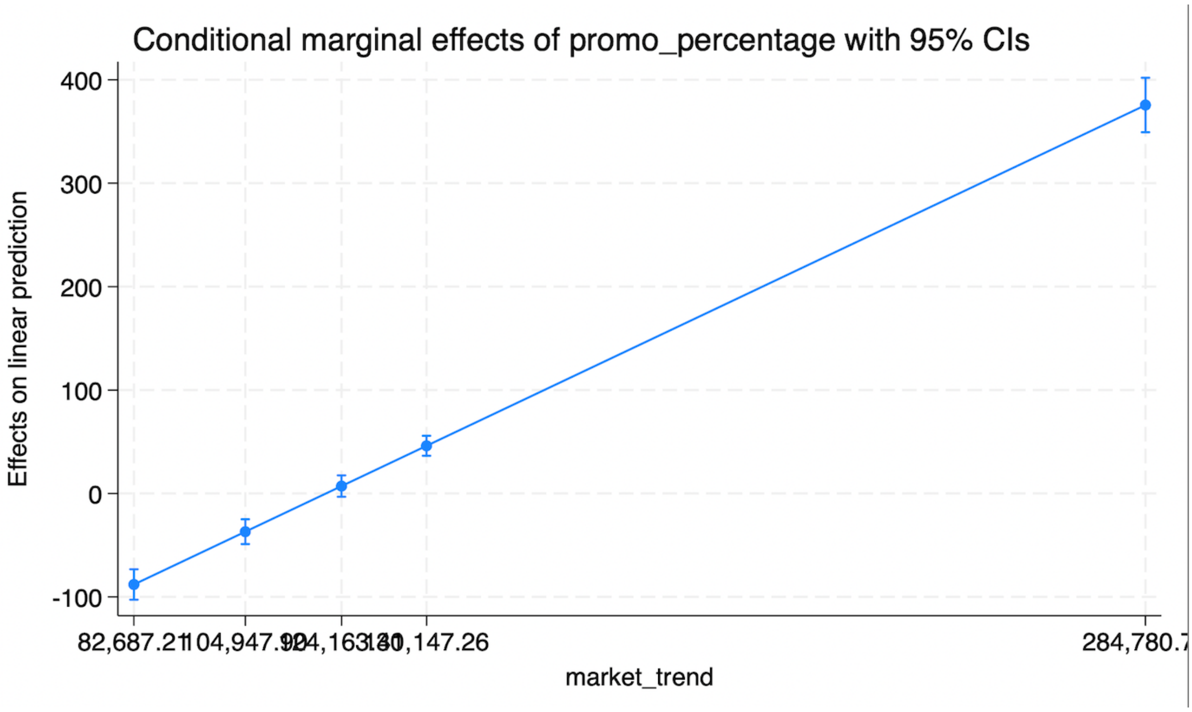


The graph illustrates the conditional marginal effects of promo_percentage on the linear prediction across various base_price levels, along with 95% confidence intervals. Notably, the effect of promo_percentage declines as the base_price increases, suggesting that promotional strategies have a diminished impact on higher-priced items. The wide confidence intervals at the extremes indicate variability in the data.

Then we analyze the margin plots for “market_trend”.

Conditional marginal effects   Number of obs = 815
Model VCE: OLS
Expression: Linear prediction, predict()
dy/dx wrt: promo_percentage

	dy/dx	Delta-method std. err.	t	P>t	[95% conf.	interval]
promo_percentage						
_at						
1	-88.070	7.499	-11.740	0.000	-102.791	-73.350
2	-36.998	6.125	-6.040	0.000	-49.019	-24.976
3	7.088	5.271	1.340	0.179	-3.258	17.435
4	46.055	4.915	9.370	0.000	36.406	55.703
5	375.593	13.419	27.990	0.000	349.253	401.933



The graph suggests that promotions are more impactful under favorable market conditions. The consistency in confidence intervals across the different ranges adds robustness to these findings, indicating that the observed effects are stable across different market states.

6. **Conclusions**

6.1 Recapitulation of key findings

The regression analyses provide a comprehensive look at the factors influencing volume sales in the context of market trends, promotional activities, and pricing strategies. Key findings indicate that promotional activities consistently enhance sales volumes across both fixed-effects and non-fixed-effects models. Market trends also positively impact sales. Interestingly, the base price's effect on sales varies between models, suggesting complex interactions between price and item-specific characteristics. Seasonality and market share have been identified as significant factors, with market share boosting sales and seasonality showing a varied impact, likely reflective of fluctuating consumer demand throughout the year.

6.2 Implications for the consumer goods sector

The regression analysis results carry significant implications for the consumer goods sector, particularly in shaping effective marketing and pricing strategies. Firstly, the consistent and significant impact of promotional activities across models underscores the power of targeted marketing campaigns in driving sales volumes. This implies that companies should invest in well-designed promotional strategies not only to attract consumer attention but also to incentivize purchases through discounts or limited-time promotions.

Moreover, the findings regarding the base price's impact on sales volumes, where the effect varies between being negative in the standard model to positive in the fixed-effects model, suggest that price sensitivity may differ significantly depending on the item and its market positioning. This variation can be instrumental for companies in segmenting their market based on consumer price tolerance. For premium products, a higher price point may not deter sales and could actually enhance perceived value, suggesting that companies might successfully implement a premium pricing strategy for high-end goods without sacrificing sales volumes.

Additionally, the influence of seasonality on sales volumes indicates that consumer goods companies need to be highly responsive to external market conditions. Anticipating seasonal shifts is crucial for adjusting inventory levels, aligning promotional activities, and timing product launches to maximize sales potential.

The significant role of market share as a positive driver of sales volumes also highlights the importance of competitive positioning and market dominance. Companies should aim to increase their market share through strategies that may include expanding distribution channels, increasing product range, enhancing customer loyalty programs, or other initiatives that strengthen brand recognition and consumer preference.

These findings suggest a strategic roadmap for consumer goods companies aiming to optimize their sales outcomes: leverage promotions effectively, tailor pricing strategies to the consumer's perception of value, align business operations with market and seasonal trends, and focus on enhancing market share to secure a dominant competitive position. Each of these strategic elements requires careful consideration of the company's specific market environment, consumer base, and product characteristics.

6.3 Recommendations for future research

For future research in the consumer goods sector, a more detailed and comprehensive exploration of the causal relationships between pricing, promotions, market trends, and consumer behavior is essential. This could involve a deeper examination of how pricing strategies impact different market segments and consumer demographics. For instance, understanding how price sensitivity varies among luxury versus budget consumers or across different age groups and regions could significantly enhance targeting and pricing decisions.

Expanding on the role of promotional strategies, it is crucial to explore their long-term effects on brand loyalty and consumer perception. Research could focus on whether short-term sales boosts due to promotions translate into sustained brand loyalty or if they potentially lead to brand dilution. Such studies could also investigate the effectiveness of various types of promotions, such as price reductions, buy-one-get-one-free offers, or loyalty rewards, and their differential impacts on consumer retention and satisfaction.

Incorporating more granular data on consumer behavior patterns would also be beneficial. This includes detailed tracking of purchasing behaviors, consumer feedback, and engagement levels across different platforms. Additionally, considering external economic factors such as changes in disposable income, inflation rates, or economic downturns could provide insights into how broader economic conditions influence consumer purchasing decisions.

Furthermore, the impact of digital marketing and online sales channels must be integrated into these models. As consumer shopping behaviors shift increasingly towards online platforms, understanding the effectiveness of digital marketing strategies and the role of e-commerce in driving sales is critical. This includes studying how online product reviews, influencer partnerships, and digital ads influence consumer choices and sales outcomes.

Expanding the dataset to include a broader array of products within the FMCG sector, beyond just margarine, would also enrich the analysis. Examining other markets such as beverages, personal care, or household cleaning products could help in identifying cross-category behaviors and strategies that are effective across the board. By broadening the scope of research to include diverse product categories, analysts can identify universal drivers of consumer behavior and tailor strategies that are effective across the FMCG sector.

Overall, these expanded areas of research could offer more robust and actionable insights, enabling businesses in the consumer goods sector to tune their strategies in response to an ever-evolving market landscape.

7. **Bibliography**

Academic references

Ali, A., & Muhammad, K. (2021). The impact of promotional tools on consumer buying behavior: A case of FMCG industry. *Journal of Marketing Strategies, 3*(1). (3)

GlobalData. (2017). *Global Executives Survey: Impact of Seasonality in FMCG Industry.* (5)

Ifeanyi-Obi, C. C., Lemchi, J., & Isife, B. I. (2008). Effect of sales promotion on the volume of sales of agro-product. *Journal of Agriculture and Social Research, 8*(2). (4)

Moisescu, O. I. (2012). A Comparative Study of the Relationship between Brand Loyalty and Market Share among Durable and Non-Durable Products. *Management & Marketing, 8*(1), 137-145. (7)

Ridgway, N. M. (1993). Price Perceptions and Consumer Shopping Behavior: A Field Study. *Journal of Marketing Research, 30*(2). (8)

Trihatmoko, R. A., & Novela, Q. A. I. (2022). Resource Allocation as Promotion Strategies for the Successful of New Products Marketing of FMCG's. *Calitatea: Acces la Success, 23*(191). (9)

Valaei, N., Rezaei, S., Bressolles, G., & Dent, M. M. (2021). Indispensable components of creativity, innovation, and FMCG companies' competitive performance: A resource-based view (RBV) of the firm. *Asia-Pacific Journal of Business Administration*. (6)

Links

NIQ's Retail Spend Barometer: https://nielseniq.com/global/en/news-center/2024/niqs-retail-spend-barometer-in-2023-italian-households-spent-e187-billion-on-consumer-goods/ (1)