# Forecasting promotional demand amidst competitor campaigns: A quantitative approach

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# Preface

Dear reader,

In front of you lies my Bachelor thesis, titled "Forecasting promotional demand amidst competitor campaigns: A quantitative approach" This research examines how competitor activity affects the RFC promotional performance and offers strategies to increase the efficiency of their promotional planning. Using advanced regression methods, I explored the relationships between variables such as discount percentages, competitor activity, and sales uplift.

This research was carried out during my internship at RFC, within the Revenue Growth Management team of Consumer Dairy Netherlands, from September 2024 to February 2025. It has been an incredibly enriching experience that has allowed me to bridge theoretical knowledge with practical applications in a dynamic business environment.

I would like to express my gratitude to all those who have supported me throughout this journey. Firstly, I want to sincerely thank my thesis supervisor, Dennis Prak, from the University of Twente, for their guidance, critical and useful feedback, and encouragement.

The author extend their thanks to RFC for providing me with the opportunity to do my thesis at their company. In particular, I am grateful to the RGM team for their mentoring, insight, and the resources necessary to carry out this thesis.

Finally, I would like to thank my family, friends, and colleagues for their unwavering support during this period. Your encouragement and understanding have been very valuable throughout this period.

I hope that this thesis not only contributes to academic literature, but also serves as a practical tool for RFCs and other organisations seeking to optimise their promotional strategies in competitive markets.

Kind regards,
Ruben van der Moere
Enschede - Amersfoort, 2025

# Management Summary

This thesis examines the impact of competitor promotions on the promotional performance of Royal FrieslandCampina (RFC) in the Dutch dairy market. The findings indicate that competitor activities, particularly from brands like Danio and Zuivelhoeve, influence RFC's sales performance. Overlapping or preceding competitor promotions result in a noticeable decline in RFC's promotional uplift. However, strategically scheduling RFC's promotions after periods of low competitor activity can lead to an increase in sales.

RFC is a large Fast Moving Consumer Goods (FMCG) company in the Netherlands with over 150 years of experience in processing dairy products. It is owned by a cooperative of 14,634 farmers and operates in seven business groups, each focusing on different global markets and specialized nutrition products. The company's brands include Campina, Optimel, and Fristi, among others, and it has a significant presence in Europe, the Americas, the Middle East, Africa, and Asia. RFC's business groups also cater to professional food industries and trade, as well as specialized nutrition for infants and active lifestyles.

Retailer-specific variations highlight the differing impacts of competitor interference on RFC's promotional performance across product categories. In the ambient category, competitor interference is most pronounced at Albert Heijn, while Boni experiences the least impact. For fresh products, Jumbo is most affected by competitor promotions, whereas Spar faces the lowest levels of interference. In the cheese category, Dirk sees the greatest impact from competitors, while Poiesz is the least affected. These insights emphasize the importance of tailoring promotional strategies to the specific competitive dynamics of each retailer.

Within the fresh product category, Campina Fresh is most influenced by Danio, with overlapping promotions causing a substantial 10 to 15 percentage point reduction in promotional uplift. In contrast, Zuivelhoeve has a smaller impact, leading to only a 4 to 6 percentage point decrease in sales. Similarly, Optimel Fresh is most affected by Danio, which reduces uplift by 8 to 12 percentage points during overlapping promotions. On the other hand, Oatly Fresh shows minimal influence, with values close to zero, indicating that data is insufficient to reliably assess its impact.

In the cheese category, Milner Cheese faces the most significant competition from Uniekaas, which causes a decline in promotional uplift by 7 to 10 percentage points during overlapping promotions. Conversely, A-ware has the least impact, with a modest 1 to 3 percentage point reduction in Milner Cheese sales.

In the ambient category, Campina Langlekker experiences minimal interference from plant-based alternatives such as Alpro and Oatly. The impact from these brands decreases gradually up to two weeks before a promotion, with a slight increase observed in week three. This suggests that plant-based alternatives have a limited effect on Campina Langlekker's promotional uplift, with their influence on the model ranging between 0.08 and 0.10. Key factors influencing promotional uplift for Campina Langlekker include deep discounts (greater than 40%), base price, number of SKUs, and base units sold, with impact values ranging from 0.13 to 0.17.

To enhance RFC's promotional planning, this study employs an XGBoost regression model trained on historical sales and promotional data. This model effectively captures the complex interactions between promotional factors and competitor activity, offering actionable insights for RFC's Revenue Growth Management team.

# Contents

# List of Figures

# List of Tables

# Glossary

**ARIMA** AutoRegressive Integrated Moving Average

**ARIMAX** AutoRegressive Integrated Moving Average with Exogenous Variables

**CDNL** Consumer Dairy Netherlands

**CPS** Competitive Pressure Score

**EDLP** Everyday low pricing

**ERP** Enterprise resource planning

**FAR** Forecast Achievement Ratio

**FMCG** Fast Moving Consumer Goods

**Incremental Units** The extra number of sales happening due to temporary events in the time period

**KPI** Key Performance Indicators

**MAPE** Mean Absolute Percentage Error

**MEPA** Middle East Pakistan & Africa

**PL** Private Label

**POS** Point of sales

**RFC** Royal Friesland Campina

**RMSE** Root Mean Squared Error

**RSP** Retail Selling Price

**SARIMAX** Seasonal AutoRegressive Integrated Moving Average with Exogenous Variables

**SDL** Self Driven Learner

**SLR** Systematic Literature Review

**UT** University of Twente

# 1 Introduction

This chapter provides an introduction to the research, offering a detailed overview of Royal FrieslandCampina (RFC) and the knowledge gaps they currently face. The importance of addressing these gaps is shown. A clear research objective is defined within a specific scope, emphasizing its relevance to both practical applications and academic contributions. Finally, the chapter outlines the expected deliverables of the research.

**Contents:**



## 1.1 Introduction of Dairy Sector

The dairy industry in the Netherlands contributes of 27.3 billion Euros (NZO-(Nederlandse-Zuivel-Organisatie), 2024) to the Dutch economy. and the consumer dairy industry has a consumer spending of 6.98 billion Euros (ZuivelNL, 2023). 59% percent of the milk produced in the Netherlands is converted into cheese. 75% of all the dairy products will be used for export (NZO-(Nederlandse-Zuivel-Organisatie), 2024). In the Dutch consumer market 75% the dairy is being sold through retailers (Agrimatie, 2024), of these retailers, the majority is bought by 3 buying groups with their respective market share: Ahold Delhaize (37%), Jumbo (21%), and Superunie (26%)(Nielsen, 2024). In the future, Dutch dairy sales are expected to be stable with a slight decline from 6.5 billion in 2023 to 6.4 billion in 2028. (NZO-(Nederlandse-Zuivel-Organisatie), 2024).

Promotions increase brand sales within the fast-moving consumer goods (FMCG) sector. RFC then establish agreements with retailers that specify the types of promotional mechanism to be used, such as “buy one, get one free” or “50% off.” The promotion reduces the price of a product for a short period and thereby increases sales volume in retailers that increase their orders in FMCG producers. The goal of retailers is to attract more retail shoppers to their stores, which they hope will buy more than just promotional items.

This thesis focuses on the commercial operations of Royal FrieslandCampina (RFC) within the Dutch market. RFC uses perceived-value pricing and value pricing strategies to align its prices with the perceived value of its products (Kotler, 2001). This approach allows RFC to have a more premium price, showing the brand’s reputation and the value it offers to customers. Furthermore, retailers themselves own brands which are called private labels (PL). PL usually adopt an everyday low pricing (EDLP) strategy, maintaining stable low prices to attract price-sensitive consumers Kotler (2001). This strategy simplifies the pricing process and builds consumer trust by offering stable, competitive prices.

## 1.2 Company description

Due to the size of the company and the wide range of departments, this section will first explain these departments and then focus on the specific department to be analysed.

### 1.2.1 Business groups

The company on which this thesis will focus is RFC. They are a large company in the FMCG sector in the Netherlands. RFC has a tradition of over 150 years of processing dairy products for farmers. Furthermore, RFC is owned by Zuivelcoöperatie FrieslandCampina U.A., which is in turn owned by 14,634 farmers based in the Netherlands, Belgium, and Germany. The company is divided into seven business groups: These are Europe, Retail & Americas, Middle East Pakistan & Africa (MEPA), Asia, Ingredients, Specialised Nutrition, Professional & Trading. The business group Europe focuses on a broad portfolio of consumer goods in European countries under their brands. In the Dutch market, these are Campina, Optimel, Chocomel, Fristi, Valess, and Friesche vlag. The European business groups has their own national based brands in Greece, Hungary, Romania, and the United Kingdom as well. Retail & Americas focuses on cheese and dairy in European countries such as Germany, France, Italy, Spain, and North and South America. Middle East Pakistan & Africa (MEPA): Focuses on consumer markets in the MEPA. Mostly based on locally produced dairy. Asia: RFC operates in various Asian consumer markets, including Indonesia, Malaysia, and Vietnam, offering a broad range of locally produced brands. The Ingredients division specializes in supplying ingredients for infant nutrition, sports and medical nutrition, and the pharmaceutical industry. Unlike other departments, this division sells its ingredients directly to manufacturers rather than retail stores.

Professional & Trading: Professionals focus on professionals in the food industry such as restaurants, bakers, and pastry chefs. The trading business involves the procurement and sale of dairy products for business-to-business selling. Specialised Nutrition: Focuses on infant nutrition under the brand name Frisco in the countries: China, Vietnam, Malaysia, Greece, and Mexico. (Royal-FrieslandCampina-N.V., 2023), (Royal-FrieslandCampina-N.V., 2024)

This thesis focusses on the business group Europe and specifically on the consumer dairy Netherlands team (CDNL). This department is responsible for the supply chain, marketing, sales and finance of the sale of the different brands that are being sold on the Dutch market. Finance manages the finances of the export; these are the products that are produced for the Dutch market but are exported to other countries. Marketing consists of different brand teams that are responsible for the brand image of each of the brands. The sales team has contact with all different customers of RFC, these mostly consist of retailers and of so-called out of home (OOH) customers. These OOH customers are mainly wholesalers.

### 1.2.2 Competitive landscape and the role of promotions for RFC

In the Dutch market, where RFC operates, the company faces competition from both branded competitors and private label brands. Branded competition of Campina and Optimel rely heavily on promotional activities of retailers in collaboration with RFC, primarily using price discounts to increase sales. These promotions are crucial to driving milk volumes, maintaining consumer relevance and staying competitive in the market. However, private label brands, owned by retailers, adopt a different strategy. They offer products at consistently lower prices, avoiding the reliance on occasional promotions.

To remain competitive, RFC must closely monitor both branded competitors and private labels. The company must adapt its promotional strategies to differentiate itself and secure favourable retail placements, ensuring that its products stand out in a highly competitive market.

Promotions are one of RFC's key strategies to drive consumer sales of its dairy products. These promotions are designed in collaboration with retailers, forming a mutually beneficial relationship. Under these agreements, both RFC and retailers share the cost burden of the promotion, and RFC typically covers a portion of the discount while the retailer absorbs the remainder. The goal of these temporary price reductions is to encourage consumers to buy more, thereby increasing sales volume at participating retail locations.

For RFC, the primary objective of these promotions is not just to attract new customers but to move large volumes of dairy products: in line with its obligation to process and distribute all the milk its member farmers produce. Regardless of market conditions or fluctuations in consumer demand, the RFC must ensure that all milk from their member farmers is processed and sold. Therefore, these promotions play a critical role in ensuring steady demand for RFC's products, minimising the risk of unsold milk that would otherwise have to be disposed of at a loss in the bulk market. By temporarily lowering prices, the RFC encourages increased consumer purchasing, effectively managing supply and demand while maintaining the profitability of its dairy products.

### 1.2.3 Promotional planning at CDNL

Promotions for RFC's products are typically agreed upon between retailers and RFC account managers. The retailer then provides the account manager with an estimate of the expected product sales during the promotional week. The account manager then inspects the expected number of products that the retailer indicated. Consequently, the account manager then sets these expectations in Visual Fabric trade promotion software (Visualfabriq, 2025), which is a promotional planning software connected to SAP (SAP, 2025); it is an enterprise resource planning (ERP) software used by RFC. The week before the promotion, the retailers can order additional products that they expect to sell during the promotion; they do this because for logistical reasons most supermarkets want to have already extra stocks: this is called forward buy (Kotler, 2001). During the promotional week itself, the final number of products will be ordered.

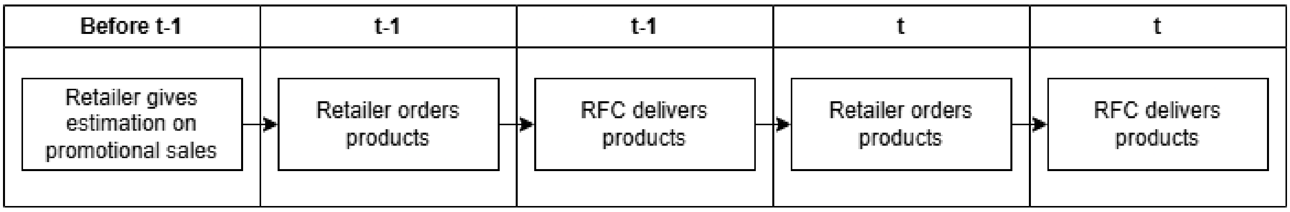


Figure 1: Chart of the ordering process before an promotional week in week t at RFC

Figure 1 shows the promotional planning as it is currently working on at CDNL, the dotted lines show the transfer of information. Promotions are coordinated between RFC account managers and retailers. However, due to legal restrictions that prohibit imposing prices on retailers (Global Legal Insights, 2024), the retailer can always change the mechanism or not play a price promotion at all. Currently, the promotions at RFC are made using the non binding retailer-provided expectations and experience from historical promotions. RFC only knows in the promotional week itself the exact number of products ordered by the retailer. Currently, RFC faces challenges in forecasting promotional sales, when competitors have promotions in the same weeks as RFC or have them in the weeks before RFC. The sales team currently cannot adjust their forecast for this, as it is unclear to what extent sales are influenced by competitor promotions. This causes several costs; these are mainly in the sales department since the products they expected to sell are not being sold, which means that the sales revenue is not as high as expected. This might not be a problem for other companies, but since milk is a perishable good, they cannot keep the milk in storage, so especially for larger retailers this will mean that the dairy which is not transformed into dairy goods sold to retailers will be sold on the secondary market. The price of this fluctuates but is lower than when the products are sold to consumers. Given the challenges RFC faces in accurately predicting promotional sales, especially in the presence of competitor promotions, it is crucial to delve into the theory of forecasting to understand how these uncertainties can be better managed and mitigated.

## 1.3 Theoretical perspective

The theory of forecasting is build on the concept that historical information can be used to forecast future events. This principle is acknowledged in various domains, including retail forecasting, where it plays an important role in the management of crucial business operations such as marketing, sales, and pricing (Petropoulos et al., 2022). Retail forecasting models, using known variables, are meant to predict future outcomes. This allows companies to optimise their operations. In the context of FMCG and retail, precise forecasting is particularly important to prepare for demand fluctuations caused by promotional activities, which are influenced by both internal and external factors. Petropoulos et al. (2022) are incorporating the impact of exogenous variables, such as competitor promotions, price changes, and seasonality, in forecasting models. This approach emphasises the interactions between promotional activities within a corporation and external market factors, such as competitor actions, that together influence consumer purchasing behaviour. The interaction among these variables can significantly influence the demand for promotional products, especially in competitive retail environments, where consumer choices are often influenced by competitor actions. Therefore, understanding the way in which competitor promotions affect consumer demand is important to improve the accuracy of sales forecasts. Building on this theoretical framework, this thesis aims to research how competitor promotions affect the promotional sales of RFC.

## 1.4 Inhibiting problems

The current challenges faced by RFC in forecasting promotional demand go beyond the typical variability in consumer behaviour during promotions. The problem is further complicated by unexpected external factors, such as competitor promotions occurring in the same week or prior weeks, which the RFC has identified as impacting sales volumes. These challenges are increased by the difficulty of generalising insights from historical promotions due to the unique nature of each event, limiting their predictive capabilities in future scenarios.

In the current situation, RFC can work with retailers on agreements to better understand the factors that influence promotional demand and help them craft such agreements. These agreements have the potential to provide transparency around competitors' promotional strategies, enabling more collaborative planning to mitigate adverse impacts.

External events, such as seasonal trends, economic shifts, and unexpected disruptions, compound the uncertainty in forecasting promotional demand. These factors often interact with competitor activities that require a more sophisticated modelling approach to accurately forecast.

The key issue, as described by the RFC, is that the current forecast method does not account for competitor interference. This limits the ability of RFC to accurately predict promotional volume, leading to inefficiencies in inventory planning and missed opportunities to maximise sales.

## 1.5 Research Approach and Methodological Framework

This section outlines the methodology and framework adopted in the research, focusing on its approach, methodology, and the anticipated deliverables as outcomes.

### 1.5.1 Problem approach

To sufficiently help RFC solve their promotional forecast problems adequately, first, there needs to be an understanding of the environment. The data sources are used to collect the data needed for the research. All of these data sources are collected from the point of sales (POS) data. The data will all be longitudinal since they will be collected over a multi-year period from Week 1 of 2022 to Week 39 of 2024. These data sources include, but are not limited to, sales data for various products, the price and promotional price of these products, the type and week of the promotions, and base and incremental split in sales data. These sources track different types of promotions used by RFC and its competitors. Using these data sources, a context analysis will first be conducted in which the following question will be explained. In the context analysis, the connection with the data sources and the data for the research will be collected as well.

To sufficiently help RFC solve their promotional forecasting problems adequately, first, there needs to be an understanding of the environment. The different data sources are used to collect the data needed for the research. All of these data sources are collected from the monitoring of sales transactions at the checkout. The data will be longitudinal since they will be collected over a multi-year period. These data sources include, but are not limited to, sales data for various products, the price and promotional price of these products, the type and week of the promotions, and base and incremental split in sales data. These sources track different types of promotions used by RFC and its competitors. Using these data sources, a context analysis will first be conducted to address the following main research question: How can RFC improve the accuracy of its promotional demand forecasting in the presence of competitor promotions to enhance revenue and operational efficiency?
**Sub-Research Questions:**

1. How does the current demand forecasting process at RFC perform in terms of accuracy per year and per segment, for promotions with competitor interference, and what is the revenue impact?

The data will be exported from IPV-data (scraping of promotion and price data from retailer websites), Nielsen (collects shopper data), and Visual-fabric (internal promotion planning and forecasting software). The data will be filtered according to the EAN code of the product, the retailers, the date, the category, and the subcategory to which these products belong.

2. What methodologies are described in the literature as critical for accurately forecasting retail promotions?

To understand forecasting, especially in the presence of competitor promotions, it is important to look at different forecasting methods. An overview of current forecast methods used in the FMCG industry will be conducted by collecting insights from academic sources. This will provide a solid theoretical foundation, enabling a comprehensive understanding of existing forecasting techniques and the integration of competitor effects at RFC.

3. Which forecasting methodology can best predict promotional retail demand while ensuring that precision is measured appropriately?

To answer this question, several steps will be taken. Firstly, a review of the models described will be conducted, and a fitting model for the available data will be selected. Based on the selected data, parameters will be defined. The raw data will be processed so that the selected model fits. Then, the model will be trained on the selected data, and the accuracy will be evaluated.

1. What are the key findings from evaluating the model's predictions of retail promotions in the presence of competitor promotions, and how do these results compare across different segments and time periods?

The dataset will be divided into training and testing subsets to develop and evaluate the model. The evaluation will focus on understanding the model's performance in predicting promotional demand under various conditions, including the presence of competitor promotions. Multiple evaluation metrics, such as RMSE (Root Mean Square Error) and MAPE (Mean Absolute Percentage Error), will be used to assess the model's accuracy. These metrics will provide insights into the model's effectiveness across different segments and time periods, highlighting areas where the model excels and where improvements may be needed. The results will be analysed to identify patterns and trends in the data, offering an overview of the model's predictive capabilities.

### 1.5.2 Deliverables

This thesis has produced three deliverables: an Executive Summary of Forecast Characteristics, a Forecast Model, and the thesis itself. The summary will include characteristics of the forecast accuracy and insights into promotional demand, highlighting differences found in various promotional depths and retailers. These outputs will be used to present a forecast model that generates real-time forecasting, including the impact of competitor promotions and precision for different types of promotions that RFC has had in the past across different periods of the year (Q1, Q2, Q3, Q4). The introduction highlighted the necessity for improved promotional forecasting.

### 1.5.3 Outline

This thesis is organized into six chapters. Chapter 2 analyzes the current situation, highlighting challenges in promotional effectiveness and the quantification of competitor impact across different dairy categories (ambient, fresh, and cheese). Chapter 3 provides a literature review on competitor promotions, promotional sales forecasting methods, relevant independent variables, and model evaluation techniques. Chapter 4 describes the methodology, including data collection, model formulation, and workflow for forecasting sales. Chapter 5 presents the results, discussing insights for different product categories and brands, such as Campina, Optimel, and Milner. Finally, Chapter 6 concludes with key findings, a discussion of implications, recommendations for RFC, and suggestions for future research.

# 2 Current situation analysis

The following subsections outline the context of the problems that the RFC sales team faces.

**Contents:**



## 2.1 Challenges in promotional effectiveness and quantification of competitor impact

In the highly competitive dairy market, RFC faces a number of challenges that inhibit its ability to fully capitalise on promotional opportunities. One of the main issues is the unpredictable nature of competitor promotions. Retailers may launch promotional activities that overlap or coincide with RFC's own campaigns, often leading to cannibalisation of promotional sales or reduced promotional effectiveness. Furthermore, the cost-sharing structure of these promotions means that RFC must carefully manage its involvement to avoid excessive losses, particularly when competitor promotions are poorly timed.

To more effectively quantify the impact of competitor promotions, we categorise these promotions according to their potential influence on each other. These categories include:

- **Ambient Dairy**: Dairy products such as ambient milk and chocolate milk that do not need cooling.
- **Fresh Dairy**: Dairy products that include quark, yoghurt, skyr, and drinking yoghurt.
- **Cheese**: A wide range of dairy-based cheeses.

The analysis covers all promotions from Week 1 of 2022 to Week 39 of 2024, providing a comprehensive view of promotional activity over time.

To quantify the influence of competitor promotions on RFC sales, we implement a weighted scoring system.

This system assigns a score based on the proximity of a competitor's promotion to RFC's own promotion:

- **24 points** if the competitor's promotion occurs in the same week.
- **12 points** if the promotion occurs one week prior.
- **6 points** if the promotion occurs two weeks prior.
- **3 points** if promotion occurs three weeks prior.

A scoring system is used to measure the extent of competitor promotions, helping identify brands and categories most vulnerable to sales losses due to competitor promotions. These points will be summed for each of the promotions, this sum will be called: Competitive Pressure Score (CPS). By understanding the potential cost impact of these interferences, we gain insights into the current implications on revenue. The system rates competitor promotions based on their recency, assuming newer promotions have more influence on RFC's sales promotions. Promotions in the same week get the most points due to their immediate impact, while points are halved each subsequent week to reflect the rapid decline in influence. This means the difference in impact between week 1 and week 2 is greater than between week 3 and week 4. Which makes sense since a promotions from a week ago will have a higher impact then a promotion from 4 weeks ago might be almost negligible.

$$\text{Forecast Achievement Ratio} = \frac{\text{Actual Sales Volume}}{\text{Forecasted Sales Volume}} \tag{1}$$

The goal is to highlight the correlation between competitor activities and sales performance, providing actionable insights for RFC's promotional strategy. Next, we will begin by analysing the impact within the ambient dairy category. Calculating the Forecast Achievement Ratio (FAR) provides valuable insights into the accuracy of RFC's promotional sales forecasts. By plotting FAR on the Y-axis and categorizing data on the X-axis, patterns in forecast performance can be identified.The previous point system will be put on the X-axis to examine their impact on forecast accuracy. A decreasing FAR with increasing competitor discounts would indicate that competitor promotions significantly reduce RFC's sales performance. Additionally, if FAR varies widely within certain conditions, it suggests inconsistencies in forecasting accuracy, highlighting areas for improvement. Visualizing this data allows for the detection of systematic biases.

### 2.1.1 Ambient

The ambient dairy brands are characterised by little direct brand competition, and promotions in this category are generally considered deep. The price decreases usually between 40% and 50% for the products promoted here.

**Campina Langlekker**

During the past three years, Campina Langlekker has captured a market share of 27.7% in the ambient milk category, while all private label (PL) brands dominate with a share of 69.3%. Arla, the largest competitor in this category, has a market share of 0.7%.

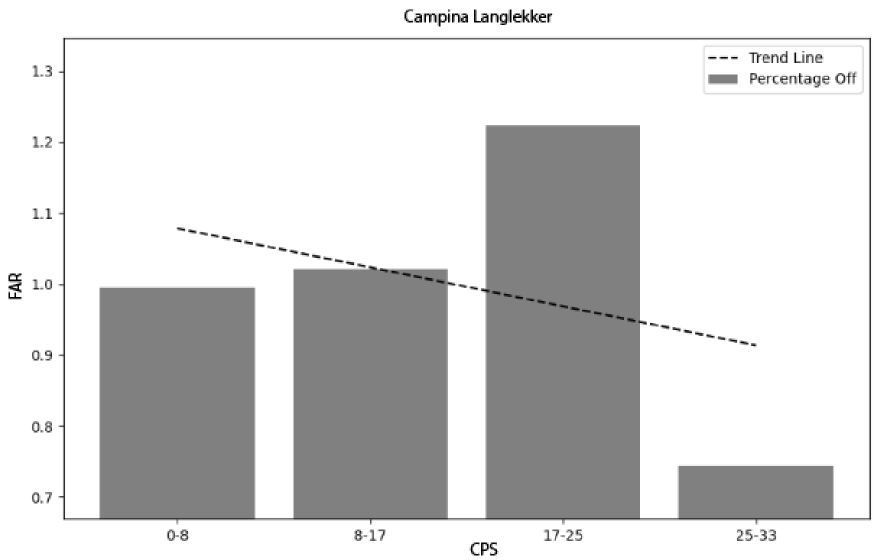


Figure 2: Impact of competitor interference on forecast accuracy at Campina Langlekker

Figure 2 shows a relationship between competitor interference and the deviation of actual sales from the forecast sales of the Campina Langlekker ambient milk brand: with higher levels of interference leading to a steeper decline in sales performance compared to the forecast. Except for the situation in the 17-25 range. The Campina will be taking into the analysis to analyse weather these are outliers or the impact is more minimal than the trend line suggest. The different CPS are taken for each promotion where the CPS falls in the range on the X axis, then the average FAR is calculated on the Y axis. This trend highlights the significant impact of competitor promotions on RFC sales during overlap or closely timed promotional periods. In the ambient milk category, direct competition from other dairy brands is negligible, as this segment experiences limited promotional activity from direct competitors. However, an influence is present from the presence of non-dairy milk alternatives, which serve as the main source of promotional competition in this category.


Figure 3: Largest influence on ambient milk promotions at Campina Langlekker

Figure 3 illustrates the three most influential brands that impact Campina Langlekker promotions, based on the calculated points in the six most influenced promotions. The six promotions which have the lowest FAR are taken and their points are summed. This gives the six promotions which have the largest decrease in sales and look at which brand would have had promotions in the same week which could influence

The analysis reveals that the primary sources of competitive pressure on Campina Langlekker originate from the brands Alpro, Oatly, and Zonnatura. These brands, which focus on plant-based products, exert the most significant influence.

**Chocomel (Ambient Chocolate Milk)**

Over the last three years, Chocomel has obtained a market share of 70.6% for ambient chocolate milk, while retail brands have a market share of 29.2 %. The biggest competitor brand in this category is Tony Chocolonely with a market share of 0.1%.

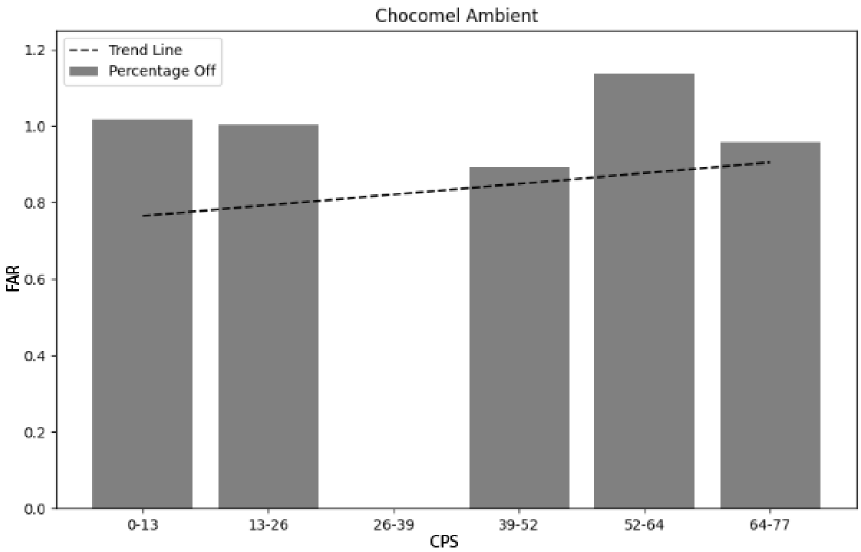


Figure 4: Impact of competitor interference on forecast accuracy at Chocomel

The strong market position of Chocomel suggests that the influence of competition is insignificant. This is reflected in the slight upward trend line observed in Figure 4, which indicates that there is no direct correlation in sales performance despite competitive activities, or even that even if competitor promotions are present people might be inclined to buy Chocomel. This stability highlights the strong position of Chocomel in maintaining its market share even in the presence of competitor promotions.

**Fristi (Ambient Fruit Drink)**
Over the last three years Fristi has obtained a market share of 37.7%, while PL brands have a market share of 37.4 %. The biggest competitor brand in this category is Bonomel with a market share of 20.9%. However, Bonomel did not have any fruit drink promotions in the last 3 years. There are other companies in the market that have a fruity drink, but their market share is not larger than 0.0% so they do not have any competition with respect to price promotions.

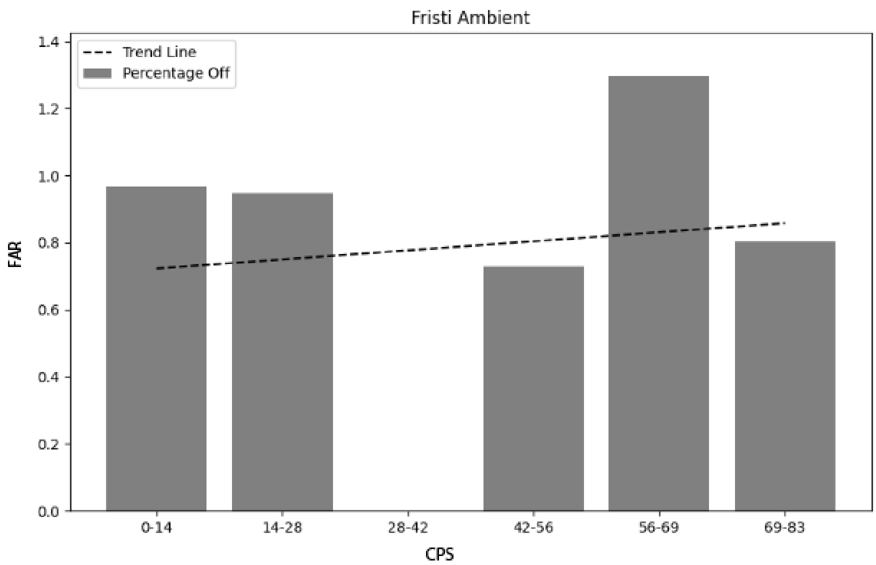


Figure 5: Impact of competitor interference on forecast accuracy at Fristi

Like Chocomel, there is a slight positive trend visible in the promotional influence of Fristi. But quite some distortion at the end, this can be explained by over or overcorrection in the estimation given by the retailers if there are any competitor promotions present. The forecast itself seems to be unaffected by competitor activity, as seen in Figure 5. This stability can be attributed to the lack of price promotions by competitors in the last three years, allowing Fristi to maintain consistent promotional performance in the fruit drink segment.

### 2.1.2 Fresh

The fresh dairy market is more segmented compared to ambient dairy, with the retailer brands holding the largest market share. The market shares of the key players are as follows: retailer brands lead with 51.7%, followed by Campina (6.8%), Melkunie (5.6%), Optimel (4.5%), Arla (4.1%), Almhof (3.6%), Alpro (2.3%), Starbucks (2.1%), Danio (2.1%) and Hipro (1.6%). This fragmentation highlights the competitive diversity in the fresh dairy segment, where retailer brands represent the largest share of the products sold, leaving branded products with relatively smaller shares.

**Campina**
Campina is the biggest dairy brand of RFC in the Netherlands, their fresh products are quark, yoghurt, custard, and butter.

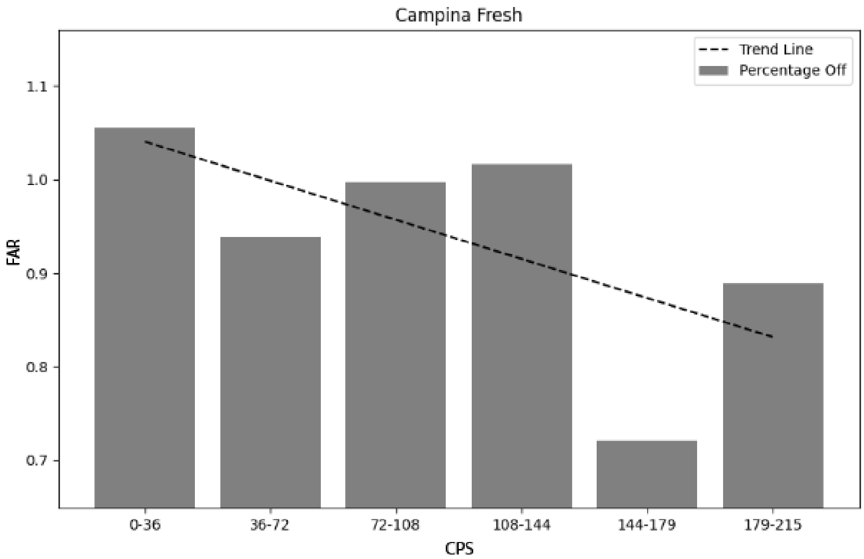


Figure 6: Impact of competitor interference on forecast accuracy at Campina

Figure 6 shows a correlation between competitor interference and the reduction in actual sales relative to the forecast sales of Campina's fresh dairy products, where elevated levels of interference correspond to a more pronounced decline in sales performance. It should be noted that initial promotions with reduced interference often exceed sales forecasts, which can be attributed to an overcorrection effect. The current model excludes considerations of competitor promotions and when such promotions are not happening, the actual sales tend to exceed the forecasts. This shows the influence of competitor promotions on Campina's sales during promotional periods. In the fresh dairy market, direct competition from other dairy brands is severe.

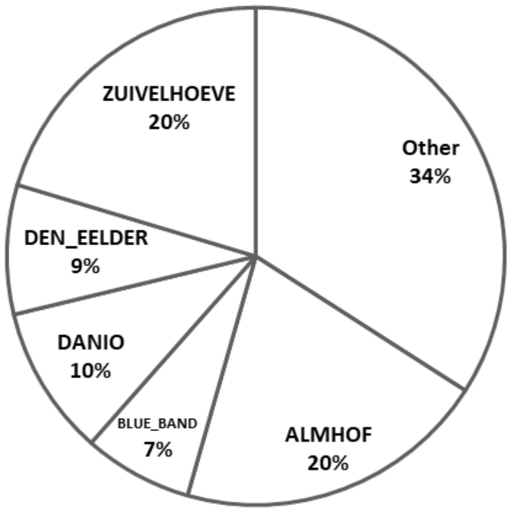


Figure 7: Largest influence on fresh dairy promotions at Campina

Figure 7 shows the five most influential competitor brands affecting the promotional performance of Campina fresh dairy products. Figure 7 shows that Almhof, owned by the German dairy company Müller, exerts the greatest influence on Campina's promotional sales volumes. This brand is known for its quark, yoghurt, and sweet desserts, which appeal strongly to consumers in overlapping market segments. The second most significant competitor is Zuivelhoeve, a Dutch dairy company with a product portfolio focused on yogurt and custard. The third largest impact comes from Danio, a brand owned by the French dairy company Danone, which specialises in flavoured quarks. Furthermore, Den Eelder has its focus on custard products, and Blue Band, a producer of butter and margarine, also contributes to competitive promotional pressures in specific subcategories, further influencing Campina's promotional results.

**Optimel**
The Optimel brand focusses on quark, drinking yoghurt, and yoghurt.

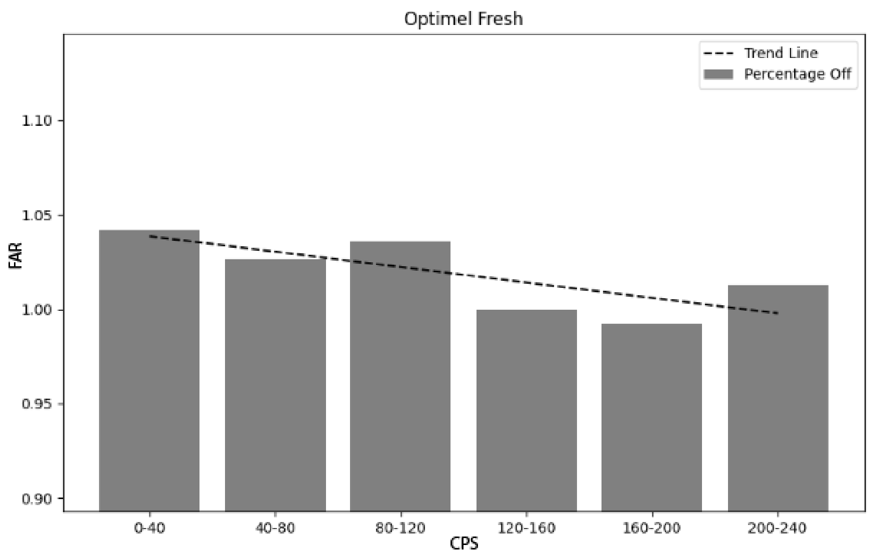


Figure 8: Impact of competitor interference on forecast accuracy at Optimel

Figure 8 shows a slight negative relationship between competitor interference and the decrease in actual sales compared to the predicted sales of Optimel fresh dairy products: Higher levels of interference lead to a stronger decline in sales performance. The FAR is all higher than 1 which can be explained by overcompensation in the explanation where the sales teams unknowingly already compensate for competitor promotions, when there are lower scores this then turns out to be overestimation. This trend shows the impact of competitor promotions on Optimel sales during overlap or closely timed promotional periods. In the fresh dairy category, direct competition from other dairy brands is more pronounced, as this segment experiences frequent and intense promotional activity from competing brands.

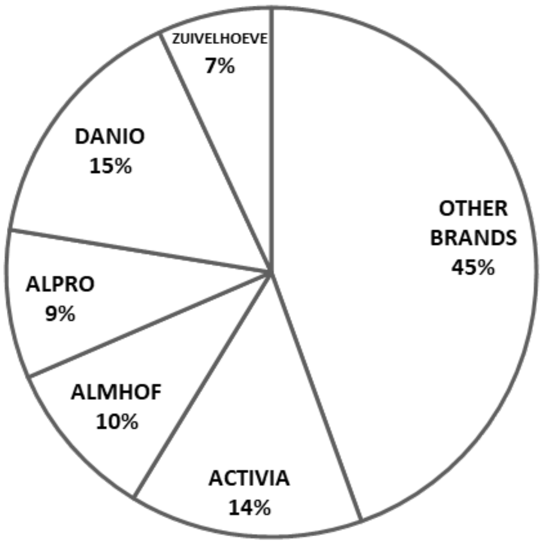


Figure 9: Largest influence on fresh dairy promotions at Optimel

Figure 9 shows the five most influential competitor brands affecting the promotional sales performance of Optimel. The analysis indicates that Danio, a brand owned by the French dairy company Danone, has the greatest influence on Optimel's promotional sales volumes. Danio specialises in flavoured quark, directly competing with Optimel's quark offerings. The second most significant competitor is Activia, also owned by Danone, which focusses on probiotic yogurts that overlap with Optimel's drinking yogurts and yoghurt products. Almhof, owned by the German dairy company Müller, is third. The company offers a diverse portfolio of yogurt, quark, and sweet desserts. Additionally, Alpro, a plant-based brand, specializes in non-dairy alternatives such as soy and almond-based yogurts. Finally, Zuivelhoeve, a Dutch dairy company focused on yoghurt and custard, also influences the performance of Optimel's promotional campaigns by competing in shared product categories.

**Mona**

The Mona brand focusses on dairy-based puddings.

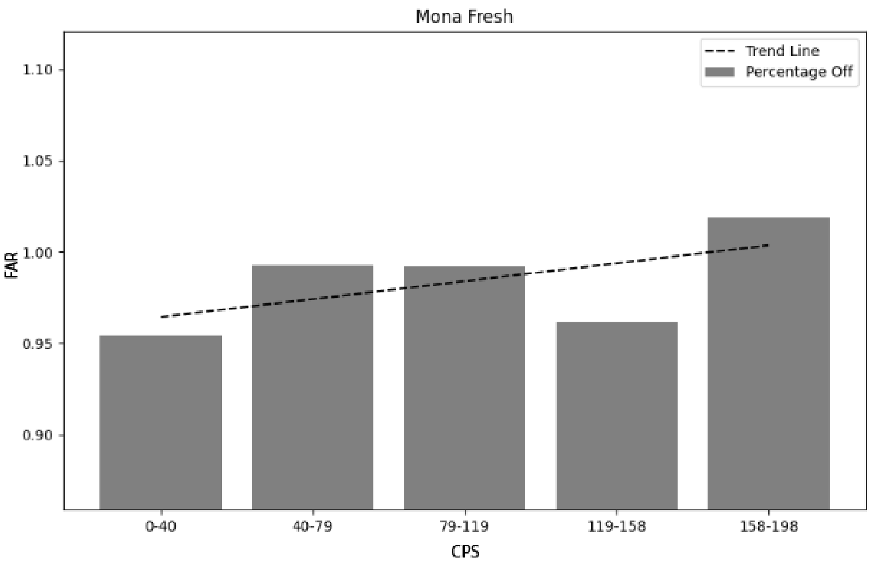


Figure 10: Impact of competitor interference on forecast accuracy at Mona

Since there is no direct competitor in the fresh pudding space, the Mona brand seems to show simmilar

### 2.1.3 Cheese

The packet cheese market is more concentrated compared to the fresh dairy market, with retailer brands holding a dominant market share of 70 2%. The rest of the market is distributed among several branded cheeses, each with relatively smaller shares. Beemster is the largest among branded products with 2.8%, followed by Eru (2.5%), Galbani (2.4%), Milner (1.9%), Philadelphia (1.5%), Uniekaas (1.3%), Old Amsterdam (1.1%), Vergeer (1.1%) and Parrano (1.0%).

**Milner** Milner, the RFCs cheese brand, focusses on selling Gouda, a traditional Dutch-style cheese.

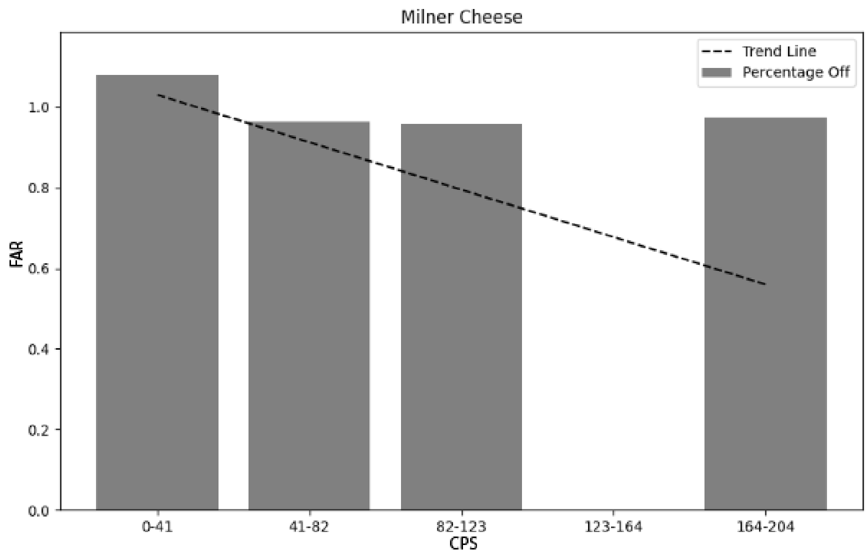


Figure 11: Impact of competitor interference on forecast accuracy at Milner

Figure 11 shows a strong relationship between competitor interference and the decrease in actual sales compared to the predicted sales of Milner cheese products. Higher levels of interference correspond to a more pronounced decline in sales performance.


Figure 12: Largest influence on cheese promotions at Milner

Figure 12 illustrates the five most influential competitor brands that affect the promotional sales performance of Milner. The analysis shows that Heks'nkaas, a brand specialising in spreadable cheese, has promotions during weeks where Milner's actual sales fall short of forecasts. Although Heks'nkaas operates in a different category, it cannot be excluded as a potential indirect influence. Uniekaas, a Dutch cheese brand offering a broad range of traditional Dutch cheeses, ranks second. Zanetti, an Italian cheese brand known for its premium hard cheeses such as Parmesan, is the third most significant competitor, reflecting competition across different product categories. Paturain, with its fresh, creamy, herb-based cheese spreads, ranks fourth, overlapping slightly with Milner's Gouda offerings. Beemster and Vergeer, both focused on Dutch-style cheese, rank fifth, sharing direct competition with Milner in the Gouda segment.

**Parrano**
Parrano, another RFC cheese brand, focusses on Italian cheese products for the Dutch market.

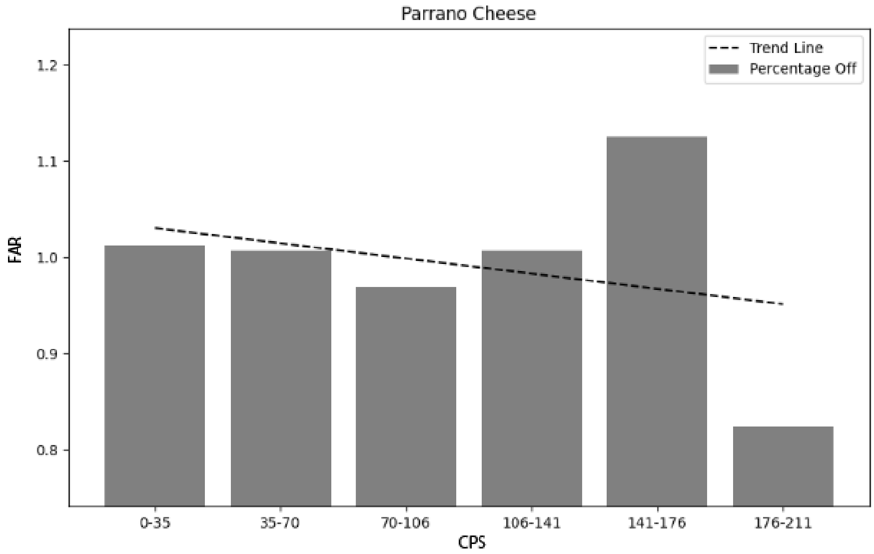


Figure 13: Impact of competitor interference on forecast accuracy at Parrano

Figure 13 shows the impact of competitor interference on forecast accuracy for Parrano cheese products. Similar to Milner, higher levels of competitor interference correlate with a decrease in sales volumes.

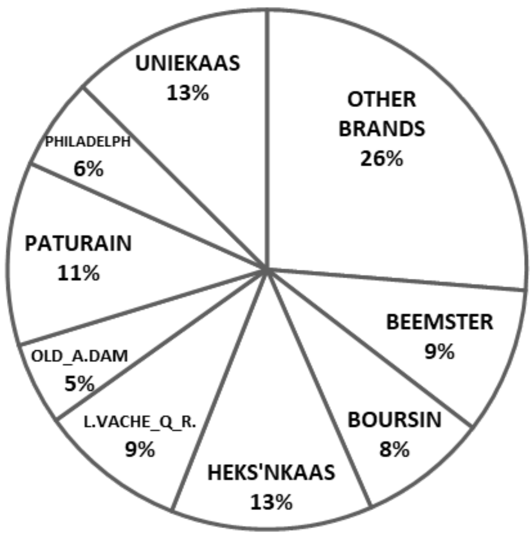


Figure 14: Largest influence on ambient milk promotions at Parrano

Figure 14 identifies the five most influential competitor brands that affect Parrano's promotional sales. Heks'nkaas and Uniekaas share the top spot with 13% influence each. Paturain, with 11%, follows closely, highlighting the competitive interaction with Parrano's Italian-inspired offerings. Beemster, another Dutch-style cheese brand, is fourth with 9% influence. Finally, Philadelphia (6%) and Old Amsterdam (5%) round out the list, showcasing competition both within the cheese segment and across complementary categories.

## 2.2 Total cost impact

Table 1 outlines the impact of competitor promotions on revenue for the all of the mentioned categorys, focussing on the Campina brand from 2022 to October 2024. The revenue loss for

| Category | Year | Amount (€) |
|---|---|---|
| Campina (Fresh) | 2022 | € -17,617.59 |
| Campina (Fresh) | 2023 | € -12,754.84 |
| Campina (Fresh) | 2024 | € -13,803.40 |
| Optimel (Fresh) | 2022 | € -22,520.27 |
| Optimel (Fresh) | 2023 | € -8,234.03 |
| Optimel (Fresh) | 2024 | € -15,121.88 |
| **Fresh Total** | | **€ -90,052.01** |
| Campina (Ambient) | 2022 | € -20,799.43 |
| Campina (Ambient) | 2023 | € 0.00 |
| Campina (Ambient) | 2024 | € 0.00 |
| **Ambient Total** | | **€ -20,799.43** |
| Milner (Cheese) | 2022-2024 | € -15,629.00 |
| Parrano (Cheese) | 2022-2024 | € -14,121.31 |
| **Cheese Total** | | **€ -29,750.31** |
| **Grand Total** | | **€ -140,601.75** |

Table 1: Impact by competitor promotions across categories (2022–2024)

this category amounts to € -20,799.43, all of which occurred in 2022, with no impact in 2023 and 2024. It is important to note that the data have been refined to exclude irrelevant or inconsistent entries, ensuring the accuracy of these figures and providing a clearer view of the impact of competitor promotions on the Campina brand.

Furthermore, Table 1 highlights the impact on the revenue of competitor promotions on the Campina and Optimel RFC fresh dairy brands during the period 2022 to 2024. The revenue loss for this category amounts to € 90,052.01. However, the data indicates that both brands were affected to varying degrees and at different time points. Campina experienced the largest revenue loss in 2022, i.e. € -17,617.59, which was in the following years, with losses of € -12,754.84 in 2023 and € -13,803.40 in 2024.

The total revenue loss of € -90,052.01 in this time period is a significant revenue loss. These results highlight the importance of understanding competitor behaviour for RFC brands Optimel and Campina.

Looking at the cheese section, Table 1 provides an overview of the financial impact of competitor promotions on RFC brands, Milner and Parrano revenue, over the years 2022 to 2024. The analysis indicates that competitor promotions have resulted in a combined revenue loss of € 29,750.31 for these brands during this period. The total impact should be viewed with caution. As the data is cleaned and refined, there is a possibility that these figures underestimate the actual financial impact. For example, certain anomalies or outliers in the data may have been excluded in the analysis. The findings underscore the need for RFC to refine its promotional strategies for these cheese brands.

The total cost impact analysis shows the financial effects of competitor promotions on the RFC brands across multiple product categories from 2022 to October 2024. As shown in Table 1, the total loss in revenue from competitor interference sums up to € 140,601.75.

## 2.3 Conclusion of the current situation analysis

The current situation analysis has found important insights for RFC's promotional strategy, particularly in understanding the impact of competitor promotions on sales performance. The analysis confirms that when competitors launch promotions just before RFC's own, there is a strong effect on sales volume. Another important finding is the limitation in forecasting accuracy. The Forecast Achievement Ratio (FAR) reveals discrepancies in RFC's promotional forecasts, particularly in highly competitive segments like fresh dairy. This indicates that current forecasting models may not adequately account for competitive dynamics, leading to suboptimal promotional planning. Additionally, the analysis highlights varying levels of vulnerability to competitor promotions across different product categories. While ambient dairy brands like Chocomel and Fristi maintain relatively stable sales despite competition, fresh dairy brands such as Campina and Optimel are more susceptible to fluctuations. By including a more nuanced understanding of competitive influence into forecasting models. RFC can better anticipate sales patterns and adjust promotional planning accordingly and the output of the model should be more accurate.

# 3 Literature Review

This chapter reviews the existing literature on forecasting promotional sales and explores forecasting methods, including traditional approaches and advanced techniques such as SARIMAX and XGBoost. The review also highlights key variables, such as price discounts and baseline sales, that can affect consumer behaviour. Finally, it discusses error metrics and model evaluation methods used to assess forecast accuracy. The purpose of this chapter is to provide a foundation for understanding the challenges of forecasting promotional sales. This can be taken into account in future chapters.

**Contents:**



## 3.1 Competitor promotions and their impact on forecasting

Price promotions are a tool for FMCG brands to increase consumer demand and convince shoppers to purchase greater quantities of discounted products. The increase in consumer demand and sales volumes has been documented by Wolters and Huchzermeier (2021). Predicting the impact of these promotions presents a challenge for both retailers and producers. The change in promotional sales forecasting comes from the wide range of variables that influence consumer behaviour (Wolters & Huchzermeier, 2021). These variables go beyond the characteristics of the promotional offer itself.(Van Donselaar et al., 2016). These include the depth of the price discount. There is a distinction made between deep promotions that are more than 40% off compared to the base price and regular promotions that are less than 40% off compared to the base price. Other factors that influence promotions are their timing and the products included in the promotion, but also external elements such as competitor promotions, which play a critical role in shaping consumer purchasing decisions.

A major challenge in promotional forecasting is understanding how competitor promotions interact with a brand's own promotional campaigns. Previous studies looked at competitor promotions to influence consumer behaviour and purchase behaviour. One of those studies is Huang et al. (2014). This research looked at the impact of competitor promotions. However, this research focused on the number of store environments in which a promotion was present. This was calculated as a promotional index. However, this approach is less relevant in markets such as the Netherlands, where promotions are generally available in all stores of a retailer. This makes the distribution of the promotion less significant as a performance indicator. Furthermore, Huang et al. (2014) studied shelf-stable products, which are different from dairy products in terms of consumer purchasing habits, since consumers can more easily stack these products in higher quantities. Dairy products, particularly fresh ones, generally have a shorter shelf life. This introduces unique dynamics not per se applicable to shelf-stable goods. Breiter and Huchzermeier (2015) incorporated consumer stockpiling behaviour into their forecasting model, assuming that consumers can buy goods in advance of a promotion and less after the promotions, which affects demand in these periods. This effect was demonstrated by Van Heerde et al. (2000), who empirically showed that promotional activities could lead to fluctuations in future demand, with an impact ranging from 4% to 25% of base sales. These findings show the role of competitor promotions in influencing immediate sales behaviour and future demand. Understanding how competitor pricing and promotional strategies shift consumer demand is crucial for developing more accurate forecasting models in the context of perishable goods, such as dairy in the case of RFC.

In the case of RFC, understanding competitor promotions is important as well as improving promotional sales forecasting. By narrowing down the impact of competitor promotions specifically on the demand for dairy products, this research seeks to fill the literature gaps. It aims to provide a deeper understanding of factors such as the depth of competitor discounts, the timing of promotions, and competitive market intensity, and how these elements affect the sales performance of RFC. By developing a more accurate forecasting model, this thesis aims to offer insights that can help optimise promotional strategies and improve inventory management, reducing the risks of stock shortages or overstocking.

Current studies on forecasting good for the perishable consumer goods such as Van Donselaar et al. (2016) often neglect the influence of competitor promotions on sales forecasting.Or, if they do consider competitor promotions, they often focus solely on shelf-stable products rather than perishable goods. This study tend to focus on the effects of the company's own promotions and therefore underestimate the competitive context in which these promotions often operate. This represents a gap in the literature.

## 3.2 Methods for forecasting promotional sales

In the FMCG sector, the forecast of promotional sales has become an essential component of promotional planning. One of the most widely used methods in this industry is the base lift method (Huang et al., 2014; Van Donselaar et al., 2016). This approach involves calculating the increase in promotional sales relative to baseline (non-promotional) sales. By separating baseline sales from incremental promotions effects, the base lift method allows companies to evaluate the impact of various factors, such as the depth of the discount and competitor actions. This method is particularly useful for understanding the extra demand generated by promotions played.

Several advanced regression methodologies have been explored. One such method is the Seasonal Auto-Regressive Integrated Moving Average with Exogenous Variables (SARIMAX), a time series forecasting technique which aims to better deal with promotional demand fluctuations. Abolghasemi et al. (2020) showed the effectiveness of SARIMAX for forecasting retail demand during promotional periods. Although its primary use is to predict sales volumes, it is used throughout the year rather than exclusively during promotional weeks. This model accommodates multiple exogenous variables, such as competitor promotions, seasonality, and external events. This helps the model to account for factors beyond the promotion itself. This helps SARIMAX to explain the broader market dynamics that influence demand during promotional periods, rather than focusing solely on internal variables such as the depth of the discount or the retailer offering the promotion.

Furthermore, machine learning techniques such as Deep Neural Networks (DNN) have shown significant results in forecasting promotional demand. Aichner and Santa (2023) highlighted the growing precision of DNN in retail demand forecasting, especially when applied to large datasets where direct relationships may not immediately be clear. In the context of promotions, this would mean identifying non-linear relationships between variables such as promotional activities, competitor behaviour, and consumer purchasing trends. Furthermore, random forest techniques, as discussed in Gür Ali and Gürlek (2020), have shown a strong performance in identifying patterns in the data that may not be immediately clear with traditional and more commonly used linear models.

The research carried out by Abolghasemi et al. (2024) shows that the XGBoost algorithm achieves a high level of accuracy in sales forecasting within promotional retail environments. The algorithm effectively reduces forecast errors, a factor of significant importance in promotional forecasting. XGBoost is good at managing large datasets and therefore capturing complex interactions between variables such as discount rates and base units. An important factor of XGBoost is its ability to calculate feature importance scores, thus identifying the primary factors that contribute to sales increases, which is important to understand promotions and not just to have black box forecasts. This interpretability improves transparency in the rationale for the model's predictions, an important requirement in retail contexts that needs justification based on evidence, not just a forecast.

## 3.3 Independent variables

A significant number of papers in the literature emphasise the critical role of choosing the right variables in improving the accuracy of these forecast models. One such important variable is the relative price discount, a measure representing the percentage reduction from the product's regular sales price (e.g., a 20% or 30% discount). The importance of this variable is consistently affirmed in articles such as Blattberg et al. (1995), Cooper et al. (1999), Van Donselaar et al. (2016), and Van Heerde et al. (2002), who regard it as the foundation for quantifying the immediate price reduction that drives consumer purchasing behaviour during promotions. This is directly related to the most basic economic principles of increased demand with lower prices.

Beyond the relative price discount, additional pricing-related variables can be found in the literature. Van Heerde et al. (2002) show the importance of including the pre-promotion price or the base price as a variable, which serves as a baseline price against which the promotional discount is given. This baseline price influences the consumer's perception of the promotion's attractiveness and therefore will have an influence on the sales uplift. Almost in this sense, Huang et al. (2014) included the logarithm of the price of competing products, as competitive pricing conditions exert a strong influence on consumer choices. This variable accounts for cross-product comparisons and helps model consumer switching behaviour during promotional periods. However, it focusses on more price points at the current time rather than the promotions of competition.

The inclusion of baseline sales is another critical aspect extensively discussed in the forecasting literature. According to Cooper et al. (1999), the baseline sales serve as an essential contextual factor to understand the overall promotional impact. These authors explain that brands can adopt divergent pricing strategies, opting for high baseline prices accompanied by frequent and deep discounts, resulting in substantial promotional boosts but low baseline volumes, or choosing lower baseline prices with less frequent or shallower discounts, resulting in higher baseline sales but reduced promotional boosts. The ability to capture these strategic differences is fundamental for accurately forecasting sales in various promotional contexts.

Additional product-specific variables have also been identified as relevant for inclusion in promotional forecasting models.Van Donselaar et al. (2016) include variables such as the number of items included in a promotion and the size of the package. The number of items in a promotional campaign indicates the size of the promotion, which can influence consumer purchasing behaviour. On the other hand, package size influences the perceived value of the product offering and can impact consumer responses to promotions. By including these variables, models can more fully reflect the product-level attributes that influence promotional outcomes.

These variables show the many variables that influence consumer behaviour during promotional periods. However, knowing these will improve the predictive power of the forecasting models. This advances both a theoretical and practical understanding of the forecasting of promotional sales of perishable goods.

## 3.4 Model evaluation methods

Forecasting models in the context of promotional sales uses a wide range of performance metrics. For example, Van Donselaar et al. (2016) use the Root Mean Squared Error (RMSE), the mean absolute percentage error (MAPE), and the mean bias to evaluate their models. These metrics are used to evaluate the magnitude of the forecast errors.

Furthermore, Huang et al. (2014) adopt multiple error metrics, including mean absolute error (MAE), mean absolute scaled error (MASE), symmetric mean absolute percentage error (SMAPE) and MAPE. These metrics offer different advantages. RMSE works better for its sensitivity to large errors and outliers, while MAPE is beneficial for its interpretability as a percentage, making it easier to understand the relative size of errors across different scales.

The wide range of evaluation metrics used in the literature shows the range of options to evaluate promotional sales forecast models. While acceptable MAPE thresholds can vary depending on the industry and context, a general classification is often used in academic literature. According to Lewis (1982), MAPE values can be categorized as follows:

- **Less than 10%** – Highly accurate forecast
- **10% to 20%** – Good forecast accuracy
- **20% to 50%** – Reasonable/moderate accuracy
- **Above 50%** – Poor forecast accuracy

In the context of promotional sales forecasting, a MAPE below 20% is typically considered good as well, as demand fluctuations due to promotions introduce higher variability (Chopra & Meindl, 2019). However, if MAPE exceeds 50%, the forecast may be unreliable for decision-making, indicating that the model requires improvement.

## 3.5 Concluding the literature

This research aligns with current studies on promotional demand forecasting, which have explored factors such as discount rates, product characteristics, and seasonality. However, there is a gap regarding the impact of competitor promotions taking place before a brand's own promotional events. Although past studies focused on internal promotions (Huang et al., 2014; Van Donselaar et al., 2016), they largely ignored how competitor promotions influence consumer choices and sales. This study fills that gap by including competitor promotions in forecasting models, focusing on their timing and intensity, especially for perishables such as dairy.

Inspired by the approach of Huang et al. (2014), this research investigates the combination with XGBoost and selects a slightly different set of variables. It uses RMSE to train the model and MAPE for accuracy comparison. By applying both metrics, the research aims to produce reliable forecasts, enabling retailers and fast-moving consumer goods companies such as RFC to optimize their promotional strategies considering both their campaigns and market dynamics.

# 4 Methodology

This chapter discusses the data sources and methodology used to analyse the impact of competitor promotions on RFC promotional uplift. The XGBoost regression model is used to predict sales performance, incorporating factors such as price, timing, and competitor discounts.

**Contents:**



## 4.1 Data collection and management

There are two major data sources used in this thesis. The data sets are collected by the Nielsen and IPV data companies and will therefore be identified by the source of the data.

Nielsen data is one of the two most critical data sources for this thesis, offering sales records from all Dutch retailers. These records include both base and incremental sales data, which will be used to calculate promotional uplift. Furthermore, the data gives information on the actual prices at which products are sold at the checkout counter, rather than relying solely on base prices which are collected from the sites of the retailers. This creates a more precise analysis of the price changes during promotional periods. Importantly, Nielsen data contain not only RFC products, but also competitors.

The IPV data set serves as another important data source for this thesis. IPV collects daily pricing information for SKUs by scraping data from retailer websites. This data set provides pricing for both RFC and its competitors. In addition to daily prices, IPV data include information on promotional activities; this includes the specific weeks in which SKUs are promoted, the promotional mechanisms used, and the depth of discounts.

| **Column** | **Source** |
|---|---|
| Data-Key | Nielsen-IPV |
| Discount_percentage_IPV | IPV |
| Base_price | IPV |
| Promotion_text | IPV |
| Base_units | Nielsen |
| Number_of_Skus | Nielsen |
| Incremental_units | Nielsen |
| Promo_depth | Nielsen |
| Brand | Nielsen |
| Year | Nielsen |
| Week | Nielsen |
| Category | Nielsen |
| Retailer | Nielsen |
| Promo | IPV |
| Uplift | Calculated with Nielsen |
| Brand_week_before | IPV and Pivoted |

Table 2: Columns and their respective data sources.

Table 2 shows an overview of the sources for each column in the combined data set used for this thesis. Nielsen data predominantly contribute sales-related metrics, such as base units, incremental units, promotional depth, and broader categorisations such as brand, year, week, and retailer. These variables are essential to understand historical sales performance and market trends. IPV contributes more to the price of the products and the details of the promotion.

The process of preparing the data for modelling involved several important steps. First, the column names in the original datasets were not uniformly formatted, leading to potential problems in the identification of the variables used.

| **Index** | **Column Name** |
|---|---|
| 0 | Ean_code |
| 1 | Year |
| 2 | Week |
| 3 | Category |
| 4 | Retailer |
| 5 | Brand |
| 6 | Base_price |
| 7 | Brands_IPV |
| 8 | Brands_Nielsen |
| 9 | Discount_percentage_IPV |
| 10 | Promo_price_IPV |
| 11 | Base_units |
| 12 | Incremental_units |
| 13 | Promotion_text |
| 14 | Promo_depth |
| 15 | Incremental_units_sum |
| 16 | Brand_encoded |
| 17 | Base_units_sum |
| 18 | Log_sales_volume |
| 19 | Log_relative_discount |
| 20 | Discount_percentage_IPV_average |
| 21 | Promo_price |
| 22 | brand-year-Week-retailer-category |
| 23 | Number_of_Skus |
| 24 | WeekBefore |
| 25 | Promo |
| 26 | Uplift |
| 27 | Pack_type |
| 28 | Subcategory |

Table 3: Standardised column names

To address this, all column names were renamed using standardised names, these names can be found in Table 3. This step will ensure consistency across the datasets in the subsequent stages of the analysis. The entries for weeks in some datasets were recorded as ranges, such as "Weeks 1-4," which posed a challenge for time series analysis. These entries were restructured to expand the range into individual rows for each week. For example, a single entry for "Week 1-4" was split into four separate rows corresponding to weeks 1, 2, 3, and 4. This transformation was crucial to ensure that each week could be analysed as a distinct time unit. The data types for some columns were changed and defined to prevent errors. The brand names in the IPV file differed from those in the Nielsen data set and would create difficulties in creating a key on which the data could be merged. To solve this problem, a mapping process was implemented to change the brands to those of Nielsen. This was done by replacing the brand identifiers in the IPV file with the corresponding names from the Nielsen data set. The key used to merge the data was constructed by combining several attributes, including brand, year, week, retailer, and category, into a single identifier. The data sets were then aggregated on the basis of this key, ensuring that all relevant variables were properly aligned. This approach allowed for seamless merging of the datasets, creating a unified dataset for analysis. To better assess the impact of competitor promotions on the RFC brands, it is necessary to align the competitor promotion data with the corresponding promotions within the same data row. This alignment is achieved by transforming the dataset in such a way that the competitor's promotion data is incorporated into the rows where promotions occur. Specifically, for each promotion, the competitor's discounts in the weeks leading up to the promotion are represented in the data set as new columns, named brand_week-before. This can for example be Arla_0. The data in these columns indicate the discount percentage offered by the competitor during the weeks prior to the promotion.

| **Brand-Year-Week-Retailer-Category** | **ABBOT_KINNEY'S-2022-16-Plus-VERSE ZUIVEL** |
|---|---|
| **Discount_percentage_IPV** | 0,5 |
| **Discount_percentage_IPV_var** | 0 |
| **Base_price** | 3,64 |
| **Promotion_text** | 50% off |
| **Base_units** | 641,14 |
| **Number_of_Skus** | 2 |
| **Incremental_units** | 4007,86 |
| **Promo_depth** | 0 |
| **Promo_depth_var** | 0 |
| **Brand** | ABBOT KINNEY'S |
| **Year** | 2022 |
| **Week** | 16 |
| **Category** | VERSE ZUIVEL |
| **Retailer** | Plus |
| **Promo** | TRUE |
| **ALMHOF_1** | 0,382857143 |
| **ALMHOF_2** | 0,293125 |
| **ALMHOF_3** | 0 |
| **Uplift** | 6,251146395 |

Table 4: Example of a row of data after processing. (Not all columns are used to train the model)

The first row of data in Table 4 shows a promotional effort by the brand "Abbot Kinney's" in week 16 of 2022, executed at the "Plus" retailer under the "Verse Zuivel" category. This promotional initiative provided a discount of 50%, based on an original unit price of €3.64. The promotion resulted in the sale of 641.14 base units, involved SKUs, and generated an incremental sales volume of 4007.86 units. The promotional depth was recorded as zero, indicating the absence of additional promotional activities, and the promotional uplift in sales quantified at 6.25. Furthermore, the initial data row contains information related to the Almhof brand's promotional activities during the weeks preceding the "Abbot Kinney's" promotion. Specifically, the Almhof brand engaged in promotional discounts with values of 38%, 29% off, and 0 3 weeks before the present promotion. The promotional strategies employed by Almhof are critical for comprehending the effect of competitor discounts on the sales increase for "Abbot Kinney's" during its promotional time-frame. In the complete dataset there are more brands present which indicate weather they have a promotion.

## 4.2 Model formulation

To calculate the impact of competitor discounts on promotional uplift and forecast sales performance, the XGBoost regression model was used. This algorithm finds patterns in the data and finds complex relationships between variables such as price discounts, timing, product categories, and promotional intensity by building multiple decision trees that explore the data from different angles.

The regression model used in this study is structured as follows: The natural logarithm of promotional boost serves as the dependent variable, as found in Van Donselaar et al. (2016). This is also explained by the natural logarithm of the base sales volume in units as found in Van Donselaar et al. (2016). Furthermore, the number of SKUs involved in the promotion (Van Donselaar et al., 2016), the price before the promotion period (Van Donselaar et al., 2016), and the percentage of discount applied (Gür Ali & Gürlek, 2020). Abolghasemi et al. (2024) found that the use of the natural logarithm stabilises variance and reflects proportional sales changes.

In addition, it incorporates competitor brand discounts that have lagged up to three weeks before the promotion, ensuring that the model accounts for direct and delayed competitive effects. Together, that will create the following variables used to train the model:

**Exogenous Variables:**

- ln(Base Volume): Logarithm of the base sales volume before promotion.
- Number of SKUs: Total number of SKUs included in the promotion.

- Price: Product price before the promotional period.
- Brand Discount$_{\text{brand}=b,\text{weekbefore}=i}$: Discount applied to brand $b$ in the current week ($i = 0$) and up to three weeks before ($i = 1, 2, 3$).

**Endogenous Variables:**

- ln(Uplift): Natural logarithm of the promotional sales uplift, representing the increase in sales as a result of the promotion.

The research by Abolghasemi et al. (2024) shows the ability of XGBoost to produce low forecast errors in promotional retail situations, making it reliable for tasks where precision is important, such as the prediction of promotional forecasts. Using feature importance scores, we can find the influence of the variables.

### 4.2.1 Model settings

To increase the predictive accuracy of the XGBoost model, it was necessary to adjust the model features to reduce the error. Abolghasemi et al. (2024) shows the usefulness of this model and shown the parameter ranges found in Table 5. The increment ranges are doubled compared to Abolghasemi et al. (2024) for increased model performance.

| Parameter | From | To | Increment |
|---|---|---|---|
| Learning Rate | 0.01 | 0.05 | 0.02 |
| Maximum Depth | 2 | 18 | 4 |
| Max Boosting Iterations | 100 | 500 | 100 |

Table 5: Hyperparameter Ranges for XGBoost model

The model was trained for each combination of category, retailer, and brand separatly. The model was optimised for all these parameters for each of these models according to these parameters.

The data set was divided into a training set comprising 80% of the data and a test set with the remaining 20%, ensuring a balanced evaluation of the predictive performance of the model. This split is most commonly used by (Joseph, 2022) and draws it justification from the Pareto principle.

### 4.2.2 Error metrics

In similar forecasting contexts, Abolghasemi et al. (2024), Van Donselaar et al. (2016), and Gür Ali and Gürlek (2020) all employ the RMSE as the primary metric to evaluate the error of predictive models. Calculating RMSE involves taking the square root of the average squared differences between the predicted and actual values, providing a straightforward measure of model performance. A lower RMSE value generally signifies a higher degree of model precision and better fit to the data.

In the model used in this thesis, RMSE is used as the error metric for all the models trained for specific combinations of brand, retailer, and product category. For every individual model trained, which corresponds to a unique set of Brand, Retailer, and Category combinations, the RMSE is calculated to measure the error of the model's forecasts. This means that RMSE is used as the objective function of the XGBoost model.

To better compare the models, the MAPE is used as a measure to compare the models in different scenarios. This is not used as an objective function because it is not smooth and cannot handle zero values well, making it unsuitable for the optimization process used in XGBoost.

## 4.3 Workflow summary

The workflow for developing the predictive model follows a structured process, beginning with data preparation and leading up to model training and evaluation. Python was used for this project due to its widespread use in data analysis and machine learning. The following workflow shows the steps taken to preprocess the data, apply the XGBoost regression model, and evaluate its performance.

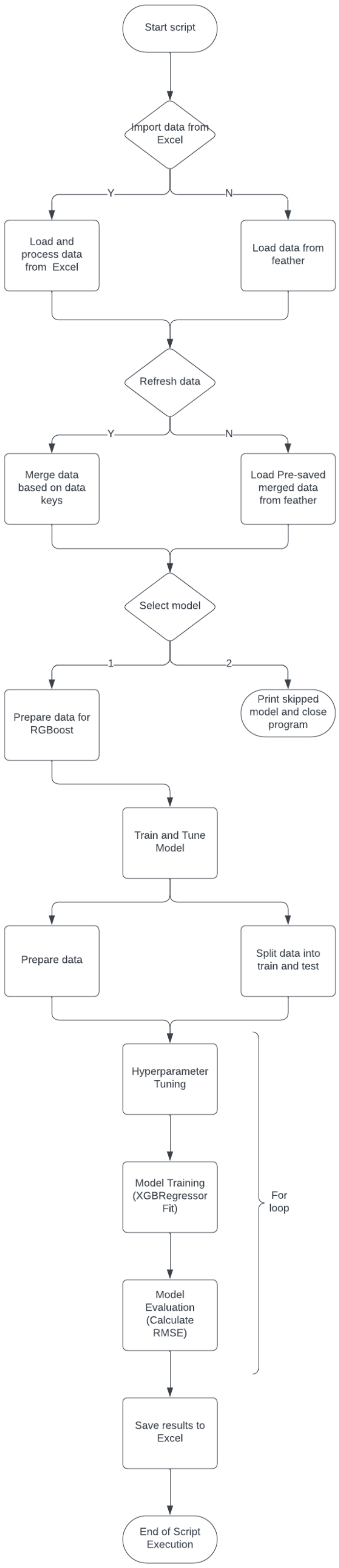


Figure 15: Flowchart of python workflow

Python was chosen for this project because of its widespread use in the field of data analysis. Furthermore, Abolghasemi et al. (2024) demonstrates the application of Python in the implementation of the XGBoost model. Several key libraries were important in the development of the model.

- **Pandas** was used for easier data management.

- **NumPy** was used for numerical operations, this includes the creation of the natural logarithms of the selected variables.

- **XGBoost** was used for the regression process.

Both the input and output processes are handled through Excel, which is done to improve accessibility and usability for the people working with the data. This integration allows team members to interact with the model's data, and results in a familiar, user-friendly environment, ensuring smooth collaboration and ease of interpretation.

The process of preparing the data and model, is illustrated in Figure 15. First, there is the option of importing the data from Excel. The data from Excel can be exported from IPV and VisualFabric. The data will then be automatically given standardised column names and the data-types will be given for easy handling. As an alternative, the data is uploaded once they are saved and can be updated later. This is the step called the feather load data in Figure 15. Feather is a light data-type which will increase usability. The next step for the user is to update the merge of the data. If this step has already happened, users can skip this step as well. If the user started the model only to update the datafiles in feather, the user can stop the programme here.

After data preparation, the data set is divided into a training set and a test set to allow performance evaluation. Additionally, standard scaling is applied, transforming the features so that they have zero mean and unit variance. Standard scaling is essential in the model to ensure that all numerical features contribute equally by normalising them to a common scale with zero mean and unit variance. This prevents variables with larger magnitudes from dominating the model's learning process and improves the stability of optimisation algorithms such as gradient boosting. By applying standard scaling, the model can learn patterns more effectively, leading to improved predictive accuracy and robustness.

Hyperparameter tuning is performed using the GridSearchCV method, which systematically tests a grid of potential hyperparameter combinations, including values for parameters such as the number of estimators, learning rate, and maximum tree depth. Cross-validation further enhances the robustness of the tuning process by splitting the data into multiple subsets and iteratively training the model in different folds to assess overall performance using the error metric RMSE.

Once the optimal parameters are found, the final XGBRegressor model is trained and the features are saved. The model's performance is then evaluated on the validation set using RMSE, providing an error measure of how accurately the model predicts promotional uplift.

Finally, the results, including the performance metrics and predictions, are exported to an Excel file for further analysis and reporting, ensuring practical accessibility for stakeholders working with the data.

## 4.4 Concluding the methodology

This chapter concludes the methodology used to analyze the impact of competitor promotions on RFC promotional uplift using the XGBoost regression model. The approach involved integrating data from Nielsen and IPV, which used sales records and promotional details, respectively. The XGBoost model was selected for its ability to capture complex relationships between variables such as price, timing, product categories, and promotional intensity. The model's dependent variable, the natural logarithm of promotional uplift, stabilized variance and reflected proportional sales changes. Key exogenous variables included the logarithm of base sales volume, the number of SKUs, product price, discount percentage, and competitor brand discounts lagged up to three weeks before the promotion.

Hyperparameter tuning using GridSearchCV optimized parameters like learning rate, maximum depth, and boosting iterations. The model was trained separately for each combination of category, retailer, and brand, ensuring tailored predictions for different market segments. The workflow, implemented in Python, involved data preparation, standard scaling, and model training, with RMSE used as the primary error metric.

This methodology provides a solid framework for analyzing promotional uplift, delivering accurate and actionable insights. The next steps involve evaluating the model's performance and interpreting the results to inform strategic promotional planning.

# 5 Results

This chapter examines the results of our analysis, focusing on how different retailers affect the forecasting of promotional uplift. We explore key factors such as deep promotions, base prices, and the number of SKUs to verify the model's general behavior and then delve into specific cases involving RFC brands. The analysis also considers the influence of individual brands and retailer-specific factors, highlighting the complex dynamics within the market.

We will discuss the varying impacts of promotions across different product categories and retailers, emphasizing how consumer behavior and stockpiling tendencies can affect forecast accuracy. The chapter will also address the different aspects of promotions, particularly how the timing of discounts influences their effectiveness.

Through this exploration, we aim to provide a comprehensive understanding of the factors driving promotional uplift and the challenges in accurately predicting these outcomes. The insights gained will offer valuable perspectives for strategic planning and decision-making in promotional activities

**Contents:**



## 5.1 Ambient

In this section, we examine the ambient category to understand the impact of competitor interference on promotional uplift. We begin by analyzing the retailers to identify general trends across all brands and different retailers. This broad perspective helps us establish a baseline understanding of how promotional activities influence sales in this category.

Following this, we look more into the Campina Langlekker to assess how competitor interference affects their promotional outcomes. By focusing on the values that determine competitor interference, we aim to find insights that can improve strategic decisions and enhance the accuracy of our forecasting models.

### 5.1.1 Retailers

In this section, we examine the impact of different retailers on the forecasting of promotional uplift within the ambient category. The analysis includes all brands, both RFC-owned and competitors, to provide a comprehensive overview. We focus on the fractions of different retailers in the created forecast, where these fractions represent the model's decision-making values. Specifically, these values indicate the relative importance of each retailer in influencing the promotional uplift as determined by the model. They reflect how much weight the model assigns to each retailer's promotional activities when predicting the uplift. Throughout the Results section, we will analyze these values to understand their implications and significance.

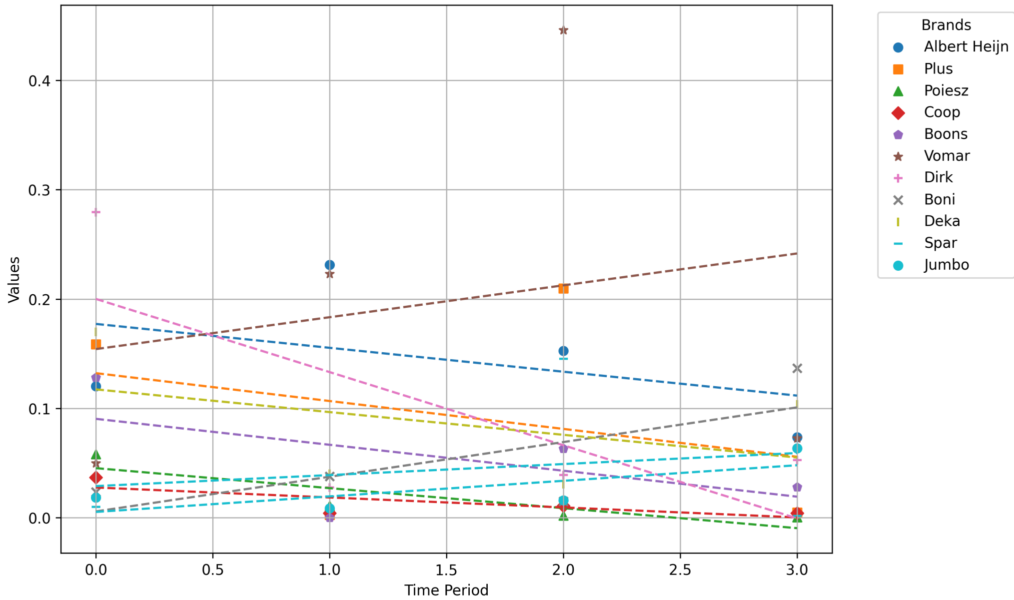


Figure 16: Impact of competitor interference on promotional uplift at the retailers in the ambient category

Figure 16 shows the results of the analysis that examines the fractions of different retailers in the created forecast. This analysis covers all brands, including those not owned by RFC, to provide a more comprehensive overview. The x-axis shows the time in weeks before the promotions, while the y-axis reflects the fraction (on a scale of 0 to 1) of the impact on the determination of the promotion uplift in the model.

The results show that not all retailers show a consistent decline in impact as the time before promotion increases. This variation can be attributed to several different factors. For example, Jumbo (which is the lowest of the two blue lines) implements seasonal discounts lasting up to four weeks, which can influence trends, resulting in upward lines for specific weeks. Such longer discount periods can overlap over all the weeks, which makes the resulting line more horizontal, altering the expected pattern. Another possible explanation could be in the misalignment between retailer promotional weeks and consumer weeks, as the data are derived from IPV, which aligns weeks based on the weeks numbers given in retailer advertisement rather than calendar weeks. This can mean that for a retailers the promotions start at Wednesday and end at Wednesday, while the sales data is collected from Monday until Sunday. This discrepancy can introduce noise into the analysis, complicating the interpretation of trends.

Furthermore, this analysis uses data from all ambient brands, including those identified in earlier assessments as being minimally influenced by competition. The inclusion of these less affected brands may dilute the observed effects of competition on brands that are more sensitive to such dynamics, leading to a general dampening of the results. This means that while this analysis does not reveal a consistent influence of competition across all ambient products, it underscores the potential for competitive effects to exist on a more case-by-case basis.

| **Retailer** | **MAPE** |
|---|---|
| Poiesz | 43.17% |
| Albert Heijn | 34.85% |
| Coop | 33.74% |
| Boni | 29.55% |
| Vomar | 29.89% |
| Spar | 25.41% |
| Jumbo | 25.34% |
| Plus | 23.94% |
| Boons | 26.31% |
| Dirk | 21.12% |
| Deka | 18.54% |

Table 6: MAPE values by retailer ambient, ordered from highest to lowest

The error range of the retailers in this analysis ranges from 18.54% to 43.17%, as can be seen in Table ??. These MAPE values reflect the variation in forecast accuracy between different retailers. Deka, with an MAPE of 18.54%, shows the highest level of accuracy of the forecasts. This suggests that the underlying model is more effective compared to other retailers in predicting the promotional uplift. On the high end is Poiesz, which exhibits the highest level of error rate, with an MAPE of 43.17%, indicating a significantly lower predictive performance.

It should be noted that the forecasting model may not account for all factors that could influence the increase in promotional sales. These could be regional demographics, economic conditions, or variations in brand loyalty among consumers. These unaccounted-for variables could explain the discrepancies in MAPE values between retailers.

### 5.1.2 Campina Langlekker

In this section, we examine the impact of competitor interference on the promotional uplift for Campina Langlekker. Specifically, we analyze how the brands Alpro and Oatly influence the forecasted promotional boost over the weeks leading up to promotional activities.

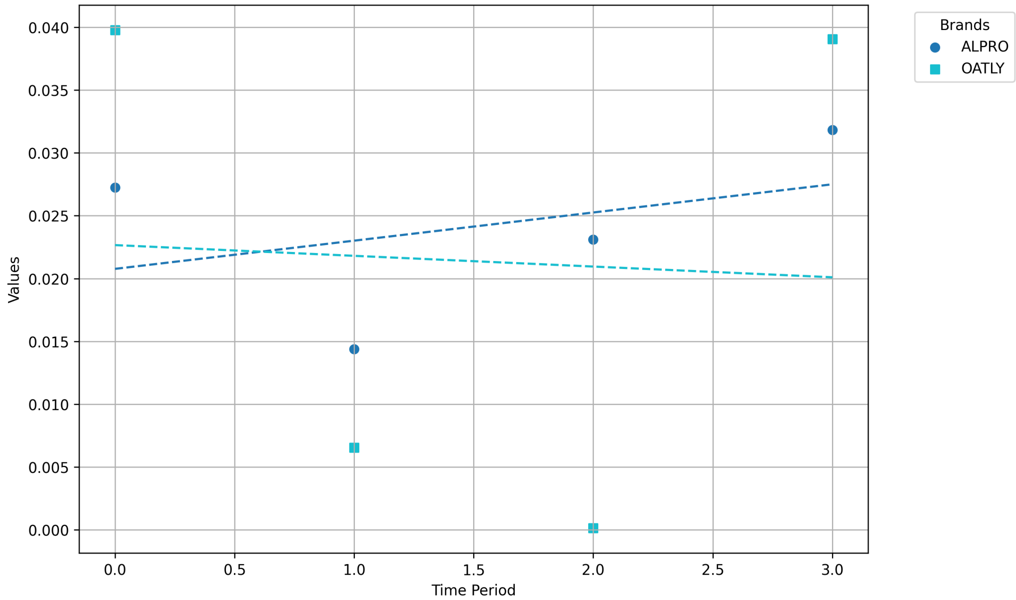


Figure 17: Impact of competitor interference on promotional uplift Campina Langlekker over the weeks before promotional activities take place

Table 17 illustrates the impact of Alpro and Oatly on the promotional boost in the forecast. The figure shows a decreasing impact up to two weeks before the promotion, followed by a sudden increase in week three. This trend suggests that while plant-based alternatives have some influence, their overall impact on FrieslandCampina's promotional uplift may be minimal.

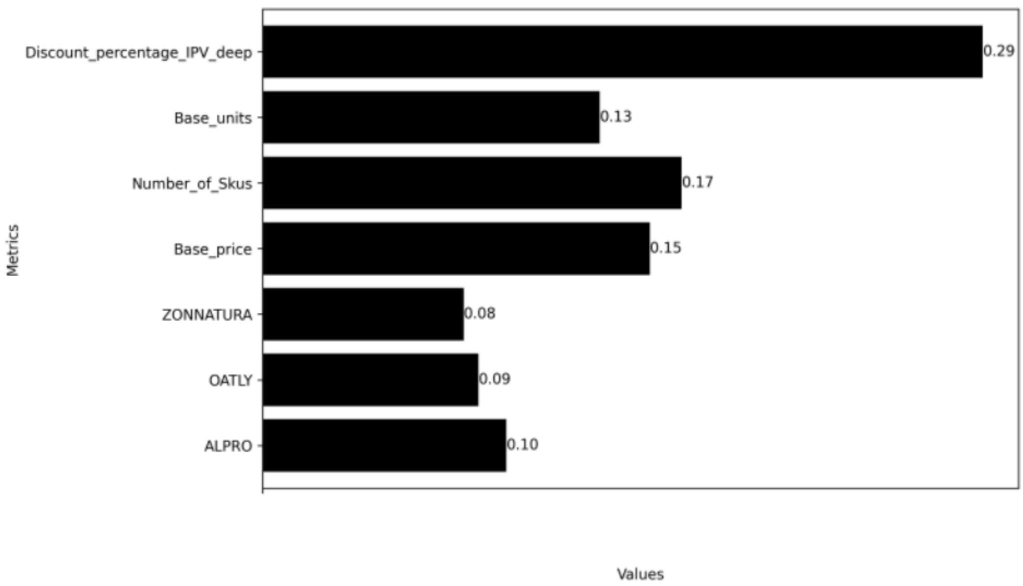


Figure 18: Impact of competitor interference on promotional uplift Campina Langlekker

The brand values are calculated as the sum of the values from weeks 0, 1, 2, and 3, reflecting the impact of various factors on the determination of the promotional uplift. The most significant factor that influences the boost is the depth of the promotion, specifically, when the discount exceeds 40% off the regular price. Other influential variables include the base price, the number of SKUs, and the number of base units typically sold, with their impact falling within the range of 0.13 to 0.17. In contrast, the three assessed brands, Zonnatura, Oatly, and Alpro, fall within a narrower range of 0.08 to 0.10. The MAPE for this forecast was 48.65%. Since this evaluation has some competition-based variables, the error rate might be high since the impact of competition seems small.

## 5.2 Fresh

Just like in the ambient category, we start by analyzing retailers to identify overarching trends across different brands and supermarkets. By taking this broader perspective first, we aim to capture general patterns in how promotions affect sales within the fresh category.

Next, we shift our focus to RFC's fresh products, examining how competitor interference influences their promotional uplift. By identifying key values that drive this effect, we aim to better understand the competitive forces at play. This two-step approach allows us to contrast market-wide trends with RFC's specific challenges.

### 5.2.1 Retailers

In this section, we analyze the impact of competitor interference on promotional uplift within the fresh category across various retailers. This analysis aims to identify patterns and discrepancies in how different retailers influence promotional outcomes.

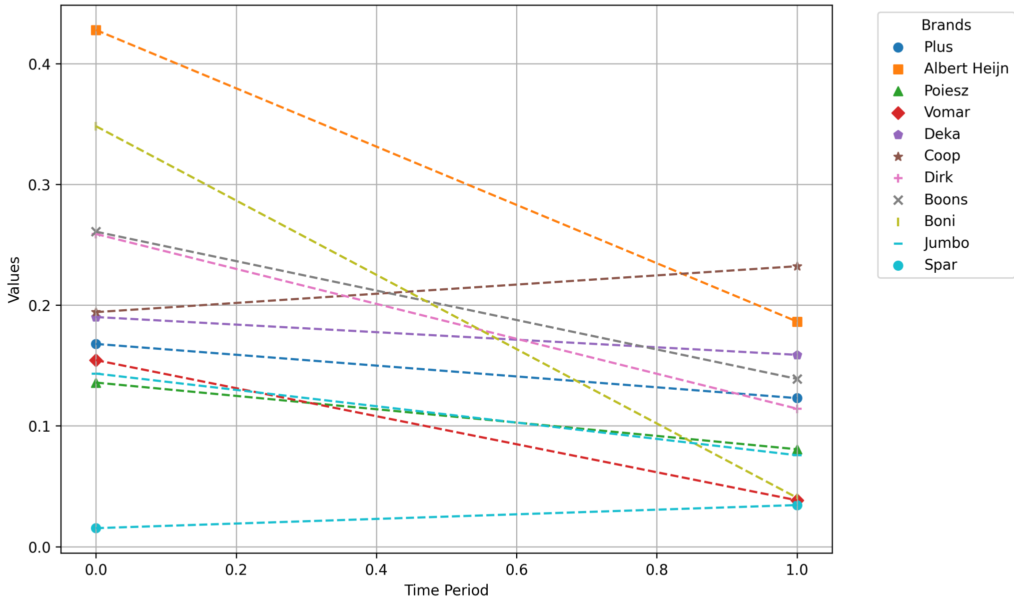


Figure 19: Impact of competitor interference on promotional uplift at the retailers in the fresh category

The retailers appear to be more aligned in this case compared to the ambient milk outcome. The only exceptions are Boons and Spar, which do not show a decreasing trend from the first to the second week. This could indicate that there is competitor interference this will be further explained in Section 5.2.2. Notably, the highest level of competitor interference is observed at Albert Heijn, RFCs largest customer in the Dutch retail market.

| **Retailer** | **MAPE** |
|---|---|
| Spar | 30.08% |
| Albert Heijn | 29.42% |
| Plus | 27.07% |
| Jumbo | 22.55% |
| Boni | 21.38% |
| Dirk | 21.16% |
| Poiesz | 21.48% |
| Boons | 18.86% |
| Deka | 18.17% |
| Vomar | 17.41% |
| Coop | 13.00% |

Table 7: MAPE values by retailer fresh, ordered from highest to lowest

Table 7 shows the MAPE values for the forecast model in the various retailers. The results show quite some variation in model performance among the different retailers. Coop has the lowest MAPE at 13.00%, indicating the most accurate predictions for this retailer. Vomar and Deka also achieve relatively low MAPE values of 17.41% and 18.17%, respectively, demonstrating good predictive performance. However, Spar has the highest MAPE at 30.08%, suggesting that the model predictions for this retailer are less accurate. Albert Heijn and Plus follow with MAPE values of 29.42% and 2707%, respectively, highlighting moderate levels of forecast accuracy. The rest of the retailers have MAPE values between 18.86% and 22.55%, showing a acceptable predictive performance. These results suggest that the accuracy of the forecast model can vary depending on retailer-specific factors.

### 5.2.2 Campina

In this section, we analyze the impact of competitor interference on the promotional uplift for Campina in the fresh category. The analysis focuses on how the timing of competitor promotions affects Campina's sales, revealing different effects depending on when these promotions occur.

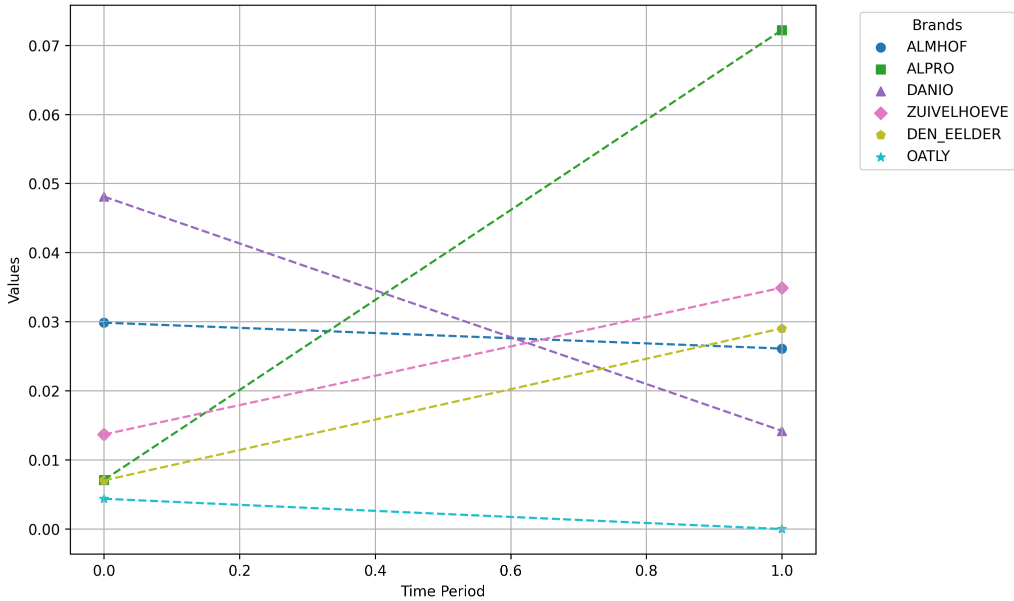


Figure 20: Impact of competitor interference on promotional uplift Campina fresh over the weeks before

The analysis of the impact of different brands on Campina promotions reveals different effects depending on the timing of competitor promotions. For some brands, the impact appears to be greater in the week immediately before the Campina promotion. For other brands, the impact is greater in the same week as Campina. This could be explained by consumer behaviour: When promotions overlap in the same week, Campina may retain its more loyal customers who prefer its products. However, if a competitor's promotion occurs the week prior, consumers are not aware of the upcoming Campina promotion and may already have stocked up on the competitor's products, reducing their need to purchase Campina products.

In the case shown in Figure 20, it seems that the Danio promotions have a stronger impact on Campina sales when they occur simultaneously, since consumers may choose Danio over Campina more frequently during this overlap. However, when Zuivelhoeve promotions occur the week before, their effect on Campina's sales seems to be smaller. This could be because consumers who purchase Zuivelhoeve in advance still opt for Campina during its promotion week. This might show a preference for Campina when both brands are promoted in the same week.

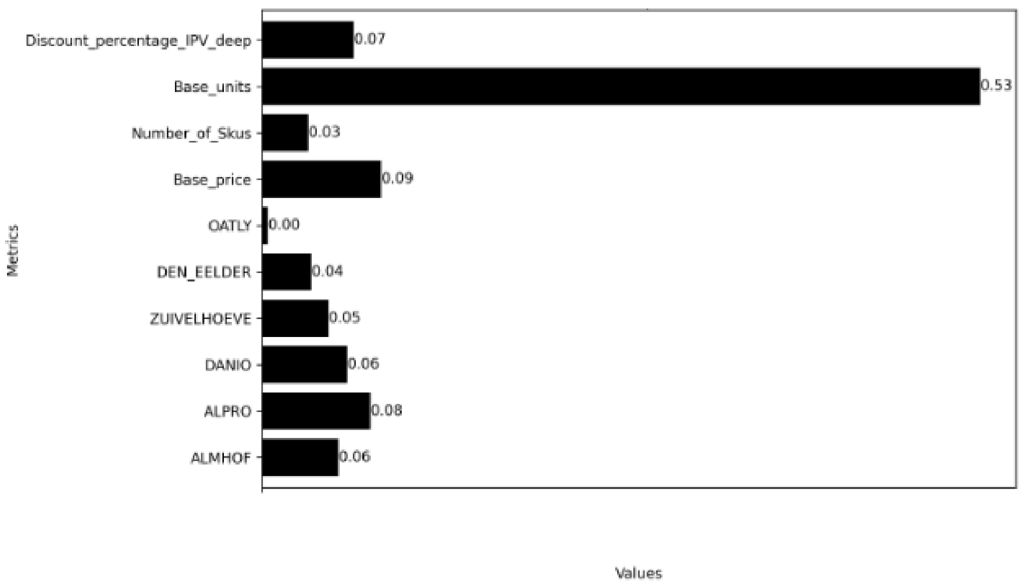


Figure 21: Impact of competitor interference on promotional uplift Campina fresh

Figure 21 shows the factors that influence the results of the forecast model. The most significant contributor is the number of base units sold, which is important to identifying the type of retailer where the promotion takes place. Other key factors include the base price and the variable representing deep discounts, both of which play an important role in shaping the forecast. In contrast, the impact of individual brands is smaller, with their contributions ranging between 0.04 and 0.08. The forecast model achieved an MAPE of 29.66%.

### 5.2.3 Optimel

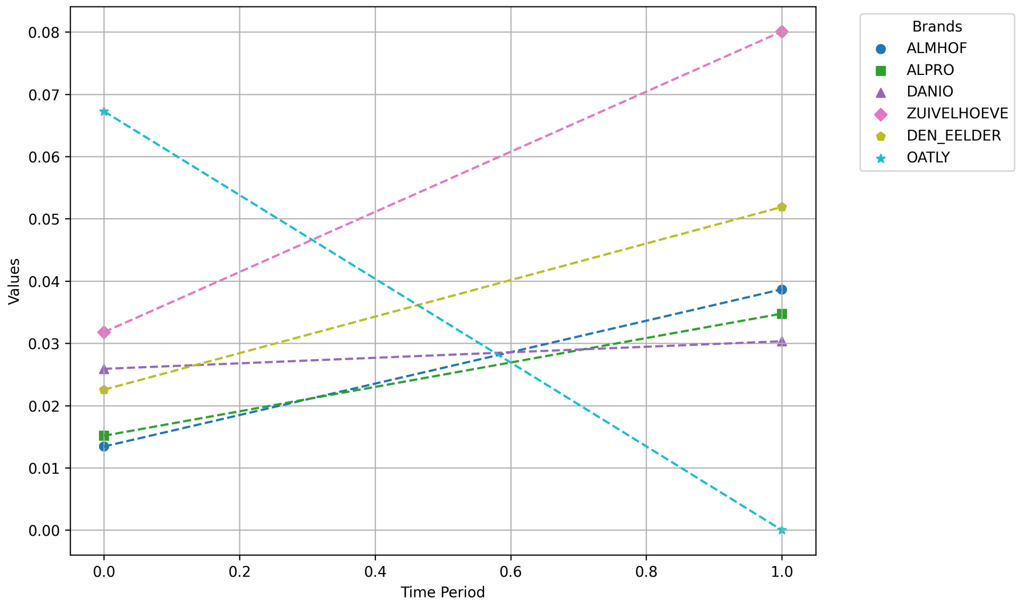


Figure 22: Impact of competitor interference on promotional uplift Optimel fresh over the weeks before

The results for Campina Fresh are similar to the finding in Campina, showing that competitor interference has a greater impact on promotional uplift in the week prior to the promotion than during the promotional week itself. This suggests that consumer purchasing decisions may be influenced more strongly by earlier promotions, possibly due to stockpiling.

However, it is important to note that the results related to Oatly Fresh are not highly reliable. The occurrence of values close to 0.0000 typically indicates that the model was unable to identify sufficient cases where an Oatly Fresh promotion took place in the week before a Campina Fresh promotion.

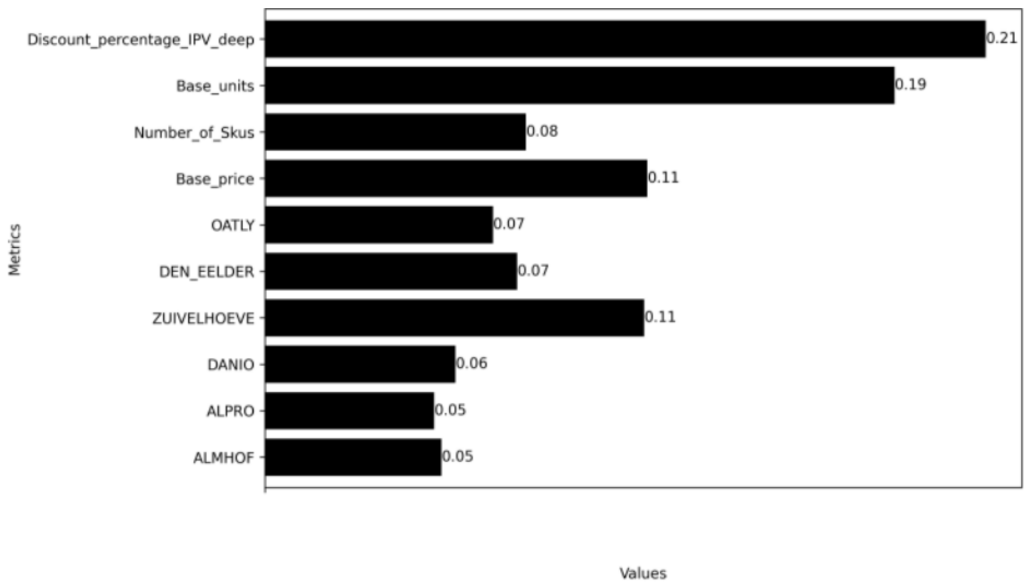


Figure 23: Impact of competitor interference on promotional uplift Optimel Fresh

Figure 21 shows the factors that influence the results of the forecast model. The most significant contributor is the factor that accounts for the deep promotions. Other important factors include the base price and the number of base units sold. The base price helps to show the relative attractiveness of the promotional discount. However, base units provide information on the underlying demand at the different retailers. In contrast, the contributions of individual brands are relatively smaller, with an impact ranging between 0.05 and 0.11. The overall performance of the forecast model, measured by the mean absolute percentage error (MAPE), is 30.24%.

## 5.3 Cheese

Similar to the ambient and fresh categories, we begin by analyzing retailers to identify general trends across different brands. This broader analysis helps establish a market-wide perspective on how promotional activities impact sales in the cheese category.

After identifying these overarching patterns, we shift our focus Milner, to examine how competitor interference affects their promotional uplift. By assessing the key values that determine this interference, we aim to gain deeper insights. This structured approach enables us to compare general market trends with the specific performance of RFC's cheese products, providing a clearer understanding of promotional effectiveness in this category.

### 5.3.1 Retailers

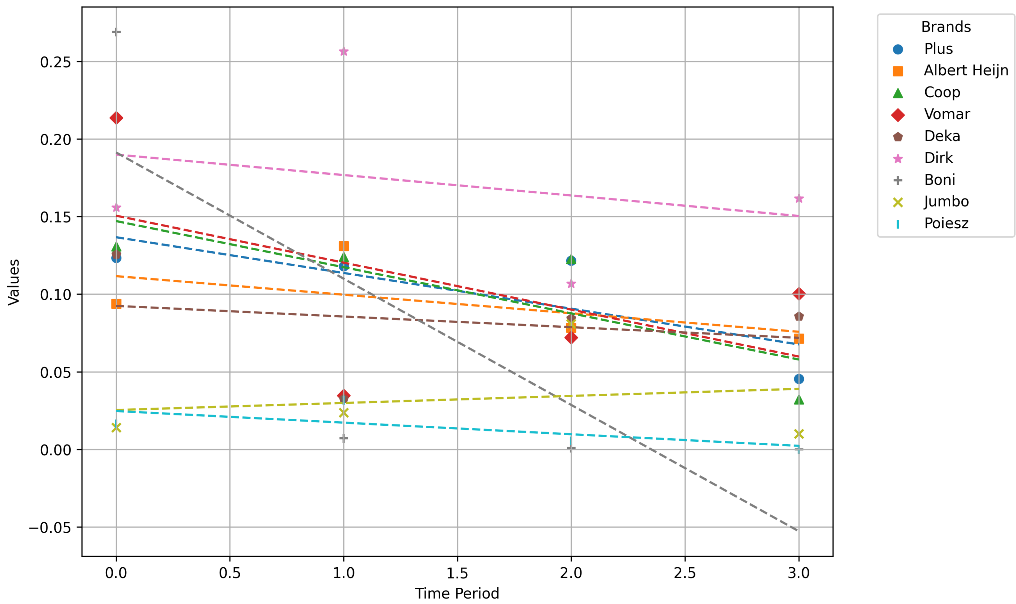


Figure 24: Impact of competitor interference on promotional uplift at the retailers in the cheese category

The impact on cheese promotions demonstrates a consistent decrease as the time interval from the promotional week increases. This trend suggests that the retailers' behaviour aligns with a logical explanation, where the influence of promotional uplift diminishes the further away it is from the promotional event. Such results highlight the effectiveness of promotions in driving immediate consumer demand, while the impact naturally fades in the preceding and subsequent weeks.

| Retailer | MAPE |
|---|---|
| Coop | 34.15% |
| Albert Heijn | 27.29% |
| Boni | 30.16% |
| Deka | 30.37% |
| Vomar | 24.70% |
| Plus | 21.93% |
| Jumbo | 18.11% |
| Spar | 14.36% |
| Dirk | 17.48% |
| Poiesz | 6.48% |

Table 8: MAPE values by retailer cheese, ordered from highest to lowest

Table ?? presents MAPE values for different retailers in the cheese category, showing variation in the performance of the model. Poiesz has the lowest MAPE at 6.48%, indicating the highest accuracy. Dirk, Jumbo, and Spar also perform well with MAPE values of 17.48%, 18.11%, and 14.36%, respectively. Furthermore, Vomar and Albert Heijn have moderate MAPE values of 24.70%, and 27.29%. Deka, Boni, and Coop have the highest MAPE values at 30.37%, 30.16%, and 34.15%, indicating a lower accuracy.

#### 5.3.2 Milner

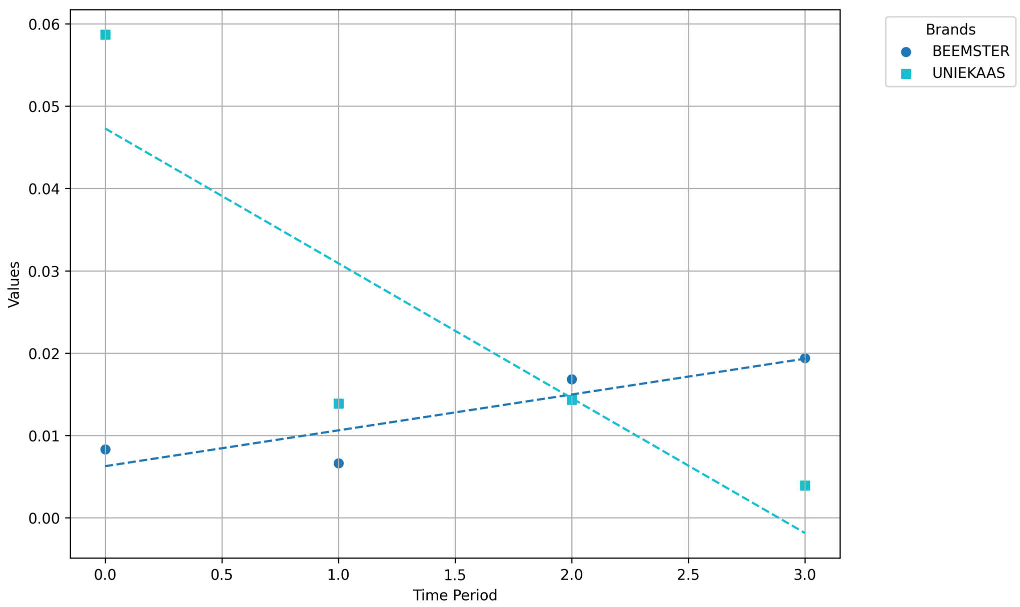


Figure 25: Impact of competitor interference on promotional uplift Milner cheese over the weeks before

It should be noted that Uniekaas has significantly more influence on promotional uplift compared to Beemster. Interestingly, this influence appears to diminish rapidly after the promotional week, with little to no impact observed in the later weeks. This pattern is somewhat unexpected, given that cheese typically has a shelf life much longer than this time frame. This suggests that consumer behaviour may be driven primarily by immediate promotional incentives rather than long-term stockpiling in the cheese space.

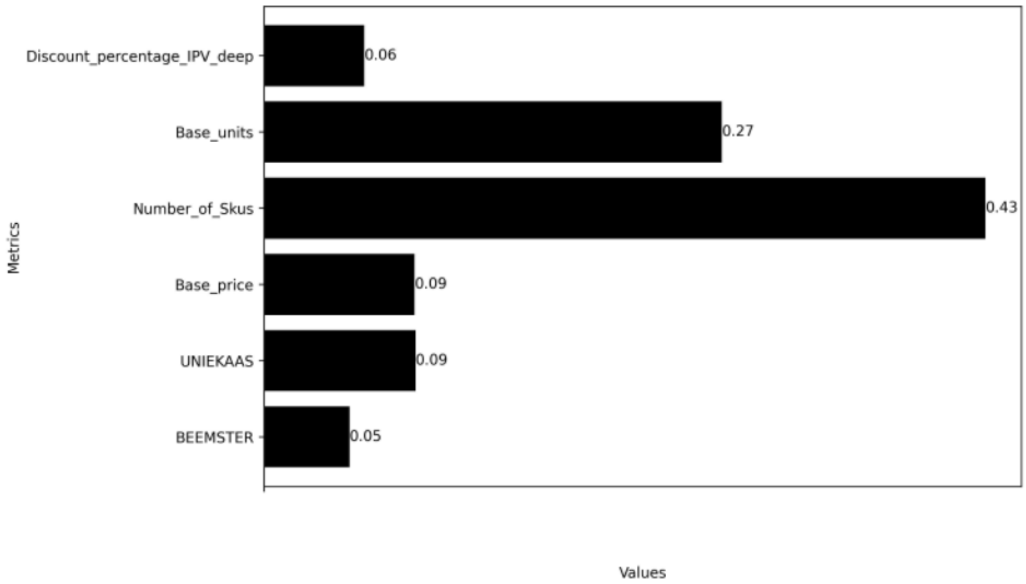


Figure 26: Impact of competitor interference on promotional uplift Milner Cheese

Figure 21 shows the factors that influence the results of the forecast model. The most significant contributor is the number of SKUs included in the promotion, which also plays a crucial role in identifying the type of retailer hosting the promotion. Smaller retailers typically offer fewer SKUs in their assortments, which can impact promotional success. Furthermore, the use of in-out promotions, where a higher number of SKUs are temporarily available, significantly affects the uplift. These promotions generate a sudden surge in sales due to the low base volume receiving a substantial boost from the inclusion of multiple SKUs.

Other key factors include the base price and the base units, both of which are important. The base price provides a measure of the relative attractiveness of the promotional discount, while the base units offer insights into the underlying demand at the retailer level. In contrast, the impact of individual brands is comparatively smaller, with their contributions ranging between 0.05 and 0.09.

The forecast model achieved an MAPE of 23.40%, indicating a reasonably high level of accuracy in predicting promotional uplift in different scenarios.

## 5.4 Concluding the results

Factors influencing forecasts include deep promotions, base price, and SKUs, while individual brands have a smaller impact. Retailer-specific factors cause variation in forecast accuracy. Campina promotions show greater impact when competitor promotions occur the week before, affecting consumer behaviour due to possible stockpiling. Factors such as the number of base units and deep discounts significantly influence forecasts. Cheese promotions see a decrease in impact as the time from the promotional week increases, highlighting the short-term effectiveness of promotions. Overall, the forecast model displays moderate accuracy across various scenarios, with MAPE values indicating the model's differing predictive capability across retailers.

# 6 Conclusion and Recommendations

This chapter presents key findings and insights from the thesis, stressing effective promotional forecasting in the Dutch dairy market. It highlights the effects of competitor promotions, retailer dynamics, and product category variations on RFC's promotional success. Conclusions emphasise avoiding overlaps with strong competitors, customising retailer strategies, and improving brand promotions for better sales and reduced waste. Recommendations include refining data integration, enhancing forecasting models, and exploring adaptive strategies to improve RFC's promotional planning.

**Contents:**



## 6.1 Conclusion

The Dutch dairy industry plays an important role in the Dutch national economy, with consumer dairy products contributing millions of euros to consumer spending. Within this competitive landscape, promotions are not just another marketing tool, but a necessity for companies like RFC to manage milk supply and demand effectively. The responsibility of the RFC to process milk from its member farmers further amplifies the importance of optimising promotional strategies to reduce wastage and increase profitability.

This thesis has contributed to the explanation of promotional forecasting in the presence of competitor interference and varying external factors. Some of the key findings showcase when the timing of the promotions are critical, but also in scenarios where this might be less of a concern. For example, overlapping promotions with competitors, such as Danio, significantly cannibalise sales during the same week. Plant-based competitors such as Alpro and Oatly might only have minimal impact on certain RFC products such as Campina Langlekker. Retail-specific insights further emphasise the need for tailored strategies per retailer when considering competitor promotions, as demonstrated by the marked differences in forecast accuracy between retailers.

The implications of these findings mean that RFCs can improve their promotional planning by avoiding direct overlaps with strong competitors, and if competitor promotions occur in the week before rather than the same week, the promotional forecast can be lowered to prevent possible problems related to lower sales than expected. Retailer-specific strategies based on forecast accuracy can further optimise resource allocation and promotional effectiveness. Furthermore, these insights provide a more solid foundation for negotiating promotional agreements with retailers, leveraging data-driven evidence to advocate for staggered promotions and fairer scheduling practices. And help increase efficiency at the sales team of CDNL by increasing knowledge on which retailers these problems are more prevalent.

Brand-level insights also create practical benefits. For example, the minimal substitution effect of plant-based alternatives suggests that RFC can focus on price-driven promotions for Campina Langlekker to maximise uplift. Similarly, targeted promotions for Milner cheese following Uniekaas discounts can capture delayed demand and mitigate competitive losses. Refinement of forecasting models by incorporating variables such as SKU variety and deep discounts will further enhance accuracy and decision making, addressing discrepancies such as misaligned consumer and retailer weeks. Sharing these insights can foster collaboration between manufacturers, such as RFC, and retailers to reduce unnecessary sales cannibalisation and improve overall market efficiency.

An important finding from this research is that the impact of competitor interference varies significantly across different product categories. In fresh dairy, overlapping promotions with strong competitors such as Danio result in immediate sales cannibalization, indicating that simultaneous promotions should be avoided. In contrast, for ambient dairy products like Campina Langlekker, the presence of plant-based competitors such as Alpro and Oatly appears to have a minimal impact, suggesting that substitution effects are limited. The timing of competitor promotions also influences promotional uplift differently across categories. While fresh dairy experiences an immediate decline when competitors promote their products in the preceding week, cheese promotions exhibit a delayed effect, with demand recovering in the weeks following a competitor's discount. Additionally, the level of competitor interference differs between retailers. Albert Heijn, as the largest customer for RFC's Dutch retail sales, shows the strongest competitive effects, while retailers like Jumbo display more stable promotional patterns.

In conclusion, this thesis provides guidance for RFCs in navigating the challenges of promotional forecasting in the Dutch market. Using these findings, RFC can achieve its goals of increasing sales volumes and decreasing waste.

## 6.2 Discussion

The findings of this study provide insightful information on the dynamics of competitor promotions and their consequent impact on RFC promotional uplift. Using a robust methodological framework anchored in the XGBoost regression model, the thesis shows the interaction of variables such as base sales, SKU numbers, discount percentages, and competitor activity in the weeks before RFC promotions. This approach not only confirmed anticipated correlations, but also revealed subtle effects of timing and competitive intensity on sales outcomes. Methodological decisions, particularly the deployment of XGBoost, proved effective in managing data complexity and capturing nonlinear relationships between variables. Including competitor discounts as lagged variables allowed the model to consider both immediate and delayed effects from competition, providing a more complete understanding of the dynamics that influence promotions. The application of MAPE as an error metric ensured that the performance of the model could be reliably tested and compared across different kinds of model which where generated. For example, comparing the forecast reliability between the retailer-level model and the brand-level models. The results showed that the degree of uplift in RFC promotional sales is influenced by competitor activity, with discounts and intensified competitor promotions that correlate with a reduction in RFC product sales.

These findings show that the timing and extent of competitor discounts play an important role in influencing consumer behaviour. Furthermore, the results also give insights that can lead to more actionable strategies for RFC to optimise its promotional planning, such as bypassing overlaps with high-intensity competitor promotions or exploiting periods of decreased competitive activity. However, this study does not come without limitations. The reliance on aggregated data and the absence of consumer-level behavioural insights imply that the model cannot fully account for individual decision-making processes or the influence of external factors, such as macroeconomic conditions. Additionally, the selection of XGBoost, although powerful, may obscure certain interpretability aspects compared to simpler models; however, the feature importance scores mitigated this issue to some extent.

While XGBoost effectively captured complex interactions, future research could look further into traditional regression methods, such as multiple linear regression or logistic regression, to improve interpretability. These models provide clearer insights into the individual impact of each variable, making it easier to explain results to decision-makers. Compared to existing literature, such as Huang et al. (2014), which shows the value of competitive information in sales forecasting, this study confirms that competitor activity can influence promotional sales. However, by incorporating lagged competitor discounts, this research extends previous insights by capturing both immediate and delayed effects.

In practical terms, the integration of this research into RFC promotional strategies has the potential to improve decision making. By discerning patterns in the data and quantifying the impact of competitor promotions, the findings can inform more targeted and effective promotional campaigns. In conclusion, this research contributes to academic understanding and practical applications in the domain of promotional forecasting. Although further research could improve the granularity and scope of the analysis, the findings provide a solid foundation for informed decision making within competitive retail environments.

## 6.3 Recommendations

Significant differences exist between retailers on the extent of competitor interference in promotional uplift. In the case of Ambient products, competitor interference is notably variable, with Albert Heijn exhibiting more substantial impacts compared to Jumbo. This is coming most probable from the fact that the promotions at Albert Heijn usually more effective are in sales volumes increase. This translates into a higher competitive interference as well. However, due to the lack of a clear trend in the weeks prior to a promotion event, the potential to influence the effect of this influence is limited, as the impact remains relatively consistent over the three-week period.

For Fresh products, the extent of competitor interference varies by retailer as well, with Albert Heijn reflecting stronger impacts than Jumbo. The timing of this interference varies between brands, and some experience more substantial effects in the week immediately preceding a promotion, while others encounter greater influence during the promotional week itself. This variation suggests the potential to incorporate difference strategies into promotional planning, adjusting approaches to suit specific brands and timing circumstances.

In the Cheese category, the differences are pronounced as well, with Dirk experiencing greater competition interference than Jumbo. Uniekaas, in particular, exerts significantly stronger influence on promotional uplift compared to Beemster. This influence decreases rapidly after the promotional week, with minimal residual impact observed in later weeks.

By understanding this retailer and category-specific behaviour, RFC can improve its promotional strategies to better address competitor interference and optimise results for each product category.

## 6.4 Limitations and further work

This thesis provides valuable information on the impact of competitor promotions on the promotional uplift of RFC using an XGBoost regression model. However, several limitations will be acknowledged here to provide some context to the findings and suggest directions for future improvements.

Firstly, the formulation of the model relies on several assumptions, such as the use of natural logarithms to stabilise variance and the inclusion of discounts from competitors that are lagged by up to three weeks. Although these assumptions are based on previous research and theoretical justifications, they may not capture all relevant dynamics in the retail environment. For example, external factors such as seasonality, weather conditions, or macroeconomic changes could also influence promotional sales, but were not explicitly considered in this study. Expanding the model to include additional explanatory variables or testing alternative modelling techniques, such as ensemble approaches or neural networks, could improve predictive accuracy.

Additionally, the XGBoost model was tuned by using a grid search with pre-defined parameter ranges. Although this approach is systematic, robust, and based on the literature, it may not guarantee the optimal performance in all brands, retailers, and category combinations due to potential overfitting or insufficient parameter exploration. Future research could experiment with more advanced hyperparameter optimisation techniques, such as Bayesian optimisation or genetic algorithms, to identify more refined parameter settings.

Finally, this research focusses mainly on analysing historical data to understand promotional dynamics. Although this provides actionable information, it does not address real-time decision making or adaptive promotional strategies. Future work could explore the implementation of a real-time forecasting system or the integration of this analysis into decision support tools for stakeholders in RFC. Such advancements could enable dynamic adjustments to promotional strategies based on changing market conditions, enhancing the practical utility of the findings.

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