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On-trade sales in beverage retail: Real case study

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"Prediction is very difficult, especially if it's about the future."

Niels Bohr

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Resumo

O estudo tem como objetivo investigar a dinâmica entre os processos de sell-in e sell-out na indústria de bebidas alcoólicas, com foco no canal on-trade no método de distribuição sell-in.

A pesquisa concentra-se em modelos de previsão que integram dados históricos de vendas e variáveis exógenas. A metodologia CRISP-DM (Cross Industry Standard Process for Data Mining) foi selecionada para conduzir o processo de análise de dados. O estudo avalia o desempenho desses modelos por meio da análise de métricas Bias e TISP, oferecendo uma compreensão detalhada da precisão da previsão, incluindo áreas de superestimação de vendas e limitações do modelo. Uma conclusão importante da investigação é o impacto significativo de variáveis externas, particularmente fatores relacionados com o turismo, como estadias em hotéis, na procura de vendas. Através dos testes de causalidade de Granger, foi estabelecido que o turismo tem uma relação preditiva com as vendas, destacando a importância da integração destes fatores exógenos nos modelos de previsão.

Os resultados demonstram que o modelo SARIMAX superou o Prophet para os top 5 SKU. Além disso, o estudo destaca os desafios associados à previsão de SKUs de baixo volume de vendas e destaca a necessidade de integração de dados em tempo real, modelos de previsão específicos para cada SKU e ajustes dinâmicos na introdução de fatores externos para melhorar a precisão.

Palavras-Chave: Modelos de previsão, canal on-trade, Bias, TISP, fatores externos, SKU

Abstract

The study investigates the dynamics between sell-in and sell-out processes in the spirits beverages industry, focusing on the channel on-trade in the sell-in distribution method.

To achieve, this research focuses on forecasting models that integrate both historical sales data and exogenous variables. The CRISP-DM (Cross Industry Standard Process for Data Mining) methodology was chosen to guide the data analysis process. The evaluation the performance of these models through the analysis of Bias and TISP metrics, offering a detailed understanding of forecasting precision, including areas of overestimation and model limitations. A key finding is the significant impact of external variables, particularly tourism-related factors such as hotel stays, on sales demand. Through Granger causality tests, it was established that tourism has a predictive relationship with sales, highlighting the importance of integrating these exogenous factors into forecasting models.

The results demonstrate that SARIMAX model outperformed Prophet for the top 5 SKUs. Additionally, the study highlights the challenges associated with forecasting low-volume SKUs and emphasizes the need for real-time data integration, SKU specific forecasting models, and dynamic adjustments to external factors for improved accuracy.

Keywords: Sales forecasting, channel on-trade, Bias, TISP, external factors, SKU

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CHAPTER 1

INTRODUCTION

The beverage industry is one of the most dynamic and competitive sectors in the global economy (Alon et al., 2011). According to Fortune Business Insights, the alcoholic beverages market was valued at 2,313.2 billion US dollars in 2023 and is projected to experience continuous growth to 5,716.2 billion USD by 2032. Large multinational companies dominate the market, offering a wide range of products, from premium whiskies to more affordable vodkas.

The alcoholic spirits beverages industry is a highly competitive and dynamic sector inside of the alcoholic beverage branch, and is characterized by a constant evolution of consumer preferences and a strong dependence on external factors, such as economic conditions and market trends. This sector operates in two main distribution methods: sell-in and sell-out. Understanding these two is crucial for manufacturers, retailers, and consumers alike. In general, sell-in refers to the sales of products from manufacturers to retailers, while sell-out relates to the sales of these products from retailers to end consumers (*Sell in vs Sell Out: A Fundamental KPI of Logistics Efficiency and Demand | POS Potential*, 2023).

This introduction sets the stage for a comprehensive analysis of the factors influencing sell-in and sell-out, the inherent discrepancies between these variables, and the strategies to harmonize both channels effectively.

Understanding and effectively managing these two distribution methods is vital to the success of companies in the beverage sector. It impacts the entire supply chain, from production and distribution to marketing and sales strategies (Kotler, P. & Keller, K. L., 2016). However, the discrepancy between sell-in and sell-out has been a significant challenge. These methods involve transactions where manufacturers sell their products to various retail entities. For example, when the volume of sell-in exceeds sell-out, retailers face problems of excess stock, which can result in additional storage costs and possible losses due to product deterioration. On the other hand, when sell-in is lower than sell-out, stock-outs occur, leading to consumer dissatisfaction and loss of sales to competing companies (Thompson, 2018).

Each of these distribution methods has distinct characteristics that influence sales, sell-in is generally driven by product distribution strategies and point-of-sale promotions, while sell-out can be affected by seasonal factors, economic conditions, and marketing campaigns (Barton et al., 2022).

Balancing "sell-in" and "sell-out" is a significant challenge for beverage companies. A study in 2017 (Ailawadi & Farris, 2017) highlights the importance of managing multiple distribution methods and the associated challenges. Christopher (2016) emphasizes that a lack of balance can result in product overstock or inventory shortages, impacting operational efficiency. In addition, is also important the division of these sales channels into on-trade and off-trade, the on-trade channel includes locations where the products are consumed on the spot, such as bars, restaurants, and hotels (Economist, 2020). In contrast, the off-trade channel involves retail distribution, for example supermarkets and liquor stores, where consumers purchase products to consume elsewhere (Euromonitor International, 2021). These two channels have distinct customer behaviors, price points and sales volumes, making it critical for companies to develop personalized approaches for each one. The ability to accurately predict end consumer demand is essential for these channels to align sell-in with sell-out. Factors such as gross domestic product (GDP), inflation, marketing campaigns and unforeseen events, such as the COVID-19 pandemic, play a significant role in determining beverage sales (Brea et al., 2020).

During the COVID-19 pandemic, there has been a substantial shift in consumption patterns, with an increase in off-trade sales and a drop in on-trade sales (consumption in bars and restaurants), exacerbating the discrepancy between sell-in and sell-out (Aswani, 2023). Another example is that a hot summer may spike the sales of refreshing drinks like gin and tonic, whereas economic downturns may lead to a decrease in discretionary spending on premium spirits (The Economist, 2020). Understanding these nuances is critical for beverage companies as it allows them to effectively adapt their strategies to meet consumer demand.

A detailed study of the drivers influencing the channels on-trade and off-trade is essential for formulating effective inventory management strategies and maximizing sales. By understanding the main factors that affect these sectors and developing predictive models for sales of different types of beverages, companies can significantly improve their ability to plan and respond to market changes.

1.1. The Discrepancy Between On-trade and Off-trade

In the competitive spirits drinks market, efficient distribution methods management is vital to any company's success. In this context, the understanding of concepts like on-trade and off-trade is important, as they determine the dynamics between manufacturers and small-scale sellers. For big alcohol beverage companies, managing this balance is particularly challenging given its diverse product range and global distribution network. The implications of these discrepancies extend beyond inventory management. They affect production planning, financial forecasting, and overall business strategy (Kotler, P. & Keller, K. L., 2016).

The balance between the sell-in and sell-out distribution is vital to avoid problems such as overstocking or lack of products on the shelves, which can damage the relationship with business partners and the end consumer's satisfaction (Christopher, 2016). However, many companies face significant challenges when aligning these two methods.

The discrepancy between the volume of products sent to sellers (sell-in) and the volume sold to the end consumer (sell-out) can result in several complications, such as excess products in warehouses, financial losses, and even brand damage (*Continuous Sell-in and Sell-out Data Analysis for a More Responsive Supply Chain*, 2023). Sales channels in the beverage industry are mainly divided into on-trade and off-trade. The on-trade channel includes bars, restaurants and hotels, where consumption is immediate. This channel is characterized by higher margins and a more controlled brand experience.

In contrast, the off-trade channel involves the sale of drinks for consumption at home through supermarkets, convenience stores, and e-commerce. This channel generally represents higher sales volumes, but with lower margins. The effectiveness of each channel can vary significantly based on factors such as geographical location, consumer demographics and marketing campaigns. When sell-in volumes are higher than sell-out volumes, retailers can face excess inventory. This excess results in additional storage costs, an increased risk of products expiring or losing value, and the potential need for discounts to clear stock. According to Kayikci *et al*., (2022) "excess inventory can lead to a reduction in profit margin due to additional storage costs and the discounts needed to sell the accumulated products".

This study aims to analyze the external drivers that influence the sell-in distribution method in the on-trade channel and to propose strategies to balance the relationship between sell-in and sell-out, contributing to more effective management in the beverage industry, more specific on the spirits industry branch, offering a holistic view of what happens in the on-trade channel of the sell-in, and to optimize this sector, consequently reducing the discrepancy between sell-in and sell-out and therefore improving a real case scenario to the next level. According to Das *et al.* (2024), aligning sell-in with sell-out is vital for operational efficiency and customer satisfaction. Discrepancies between these two can lead to financial losses and operational challenges. To mitigate these problems, companies must employ strategies that ensure a balance between the two.

In this way, research will be carried out guided by a thorough analysis of sales data of on-trade channel gathered between 2013 and 2024, and through a review of practices in the beverage industry and on the spirit's branch. This study will employ forecasting methods, using the historical data and predictive analytics, with the goal to help to anticipate demand more precisely (Boone *et al*., 2019). With this, it is expected to contribute to developing strategies that not only mitigate the discrepancy between sell-in and sell-out, but also strengthen the company position in the market, ensuring a better allocation of resources and greater consumer and customer satisfaction.

1.2. Drivers of on-trade Demand

The factors determining the on-trade channel are varied and complex, and understanding these drivers is essential for accurate forecasting and a proper strategic plan. These drivers include several external variables that companies can't control, for example, the country's GDP, inflation, sales and consumption seasonality, extraordinary events, such as the COVID-19 pandemic, and weather conditions. Studies show that GDP and inflation have a direct correlation with alcohol consumption (Statista, 2021). Consumption seasonality also plays a crucial role, with peaks in consumption observed during festive periods such as Christmas and New Year. In addition, events like the COVID-19 pandemic have drastically altered consumption patterns, significantly increasing off-trade sales while the on-trade channel has suffered.

Understanding the interactions between sales and external variables is crucial to developing and improving the channel on-trade performance.

1.3. Objectives

Therefore, this study's objectives include analyzing the main drivers of the on-trade channel in the beverages spirits industry and identifying and predicting sales of different types of drinks based on the drivers identified.

The first objective aims to identify and understand the external factors that drive sales of products directly to end consumers.

The second objective focuses on developing predictive models to estimate future sales of different beverage categories. Using the drivers identified, these models will help the industry to better plan production and distribution, aligning sell-in with sell-out.

To achieve these objectives, the study sets out to answer the following research questions: What are the main external factors influencing the sector on-trade of the sell-in distribution method in the spirits industry? What forecasts models can be made for sales of different types of drinks? How can the discrepancy between sell-in and sell-out be mitigated?

To address these questions, the next chapter offers an overview of the relevant concepts for the base of this research. The Chapter 3 details the methodology, that includes the treatment of the dataset and the outliers, selection of the forecasting modeling, the approached for the hyperparameter tuning used, and the formulas that are going to be used to measure the accuracy of the models. Chapter 4 presents the results and analysis based on the methodology, followed by Chapter 5 with a discussion of the results and on the Chapter 6 completes the thesis outlining the limitations found and suggesting future research directions.

CHAPTER 2

Literature Review

Effective management of the sell-in and sell-out methods is crucial, especially in the spirits beverage sector. One of the biggest challenges to proper sales success is to have harmony between the sell-in and sell-out and to find a way to balance them. In sectors like retail, e-commerce, and consumer goods, predicting future sales is fundamental to remaining competitive (Mentzer & Moon, 2004). This literature review addresses a way to balance these methods, searching techniques of forecasting sales, and how that plays a crucial role in this type of company, and how to find that balance between those two, focusing on the on-trade channel.

2.1. Literature Collection

The data collection process was done with the help of different electronic databases such as Scopus and Google Scholar, where they were systematically searched using a combination of key terms, including: Sell-in; Sell-out; Forecasting; Beverage retail.

The query that was used on Scopus was: (TITLE-ABS-KEY (sell AND in AND sell AND out) AND TITLE-ABS-KEY (forecast) OR TITLE-ABS-KEY (sell AND in AND sell AND out AND machine AND learning)) AND (LIMIT-TO (EXACT KEYWORD, "Forecasting") OR LIMIT-TO (EXACT KEYWORD, "Sales") OR LIMIT-TO (EXACT KEYWORD, "Commerce")

The query used was considered to capture articles and publications that precisely addressed the relationship between "sell-in" and "sell-out" dynamics while placing a substantial emphasis on forecasting techniques on the beverages market. Additionally, the term "machine learning" was used to explore the different methodologies within the context of sales forecasting.

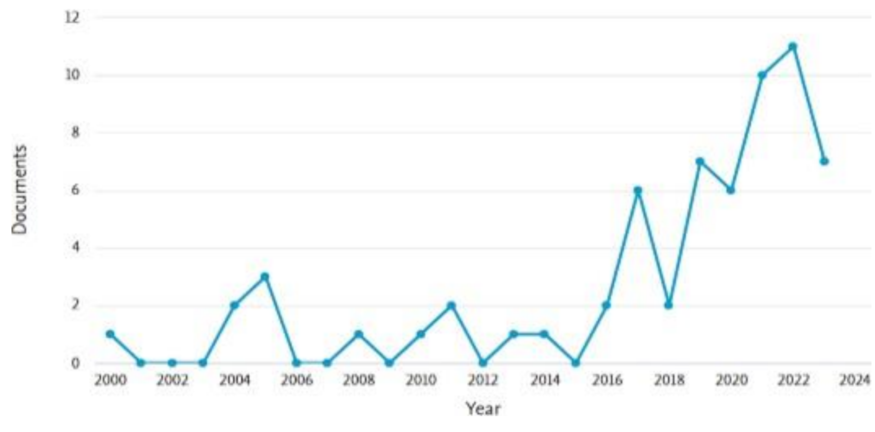

Figure 2.1 Results of articles across 200-2024 referring to sell-in" and "sell-out", "forecasting techniques" and "machine learning"

The search results of the query below conducted on the Scopus database returned a total of 90 articles, within the periods of 2000 and 2024, about the dynamic domain of sales strategies, forecasting methodologies, and the relationship between "sell in" and "sell out" practices within the commercial sector.

The first years of the analyzed period exhibited a few representations of articles on these topics. However, a pronounced surge in scholarly contributions has become visible in the latest years of the search, signifying an increased interest in the scientific topic.

Following the initial search, the titles and abstracts were read and analyzed based on the inclusion and exclusion criteria, as recorded in Table 1 and Table 2. The inclusion criteria for this systematic literature review focus on selecting studies that directly addressed the fundamental aspects of "sell-in" and "sell-out" dynamics within the context of retail products, with information about the understanding of external factors that impact sales performance and market positioning strategies. The exclusion criteria were designed to exclude articles based on the article's availability and duplicate articles. They also excluded articles with irrelevant research topics from the topics mentioned and with a lack of clear focus on sales strategies.

Table 1 - Inclusion Criteria

Inclusion Criteria
Direct Addressing of Sell-in and Sell-out Dynamics
Relevance to Alcoholic Beverages or Beverage Products
Articles with relevant abstract for the study

Table 2 Exclusion Criteria

Exclusion Criteria
Limited Full-Text Availability
Duplicate Articles
Irrelevant Research Focus
Lack of Clear Focus on Sales Strategies

2.2. Drivers in the alcoholic beverage industry

Identifying the main drivers of sell-out is essential to understand the factors influencing consumer demand and product sales. Studies like Telukdarie et al. (2020) and Pascucci et al. (2022) highlight various factors that can affect sell-outs in the beverage industry, including economic conditions, consumption seasonality, marketing campaigns, and unforeseen events, such as the COVID-19 pandemic.

Studies show several external factors that can influence both the performance of the sell-in and sell-out (Muthiani, 2015). One of these factors is a country's economic performance, measured by indicators such as GDP and inflation, which play a crucial role in beverage consumption (Olarewaju & Folarin, 2012). For example, during periods of economic growth, consumers tend to spend more on premium beverages and social occasions, consequently increasing sales in the off-trade channel. Conversely, during economic recessions, there is a tendency to shift to cheaper brands and a general decline in spirits beverage sales (Dekimpe & Heerde, 2023).

Other external factors like weather and precipitation significantly determine beverage consumption. Additionally, holidays and seasonal events, such as Christmas and New Year, can boost sales of specific beverage categories. A study made by the company being researched on these study, case of 2020 revealed that rum sales significantly increased during summer celebrations, especially in tourist regions.

To combat the seasonal sales discrepancy influenced by these external factors, companies use tools like marketing campaigns, promotions, and events, which are crucial for stimulating the sell-out distribution method. The strategic distribution of resources for advertising campaigns and discounts during periods of high demand can maximize sales. An example is holding promotions and tasting events in stores during the summer months to increase sales of refreshing beverages.

Another external factor, such as the COVID-19 pandemic, drastically changed spirits beverage consumption patterns. The closure of bars, restaurants, and nightclubs during lockdowns forced an increase in sell-out for home consumption, creating a significant discrepancy with sell-in (Nielsen, 2020). This phenomenon highlighted the need for flexibility in sales and marketing strategies to adapt to rapid changes in consumer behavior.

One way for companies to adapt to the consequences of controllable and uncontrollable external factors is the implementation of information system technologies. A study (Schmidt, 2022) showed that these systems can improve supply chain visibility, helping balance sell-in and sell-out through better decision-making. Lee and Billington (1992) also argue that technology can help mitigate inefficiencies in inventory management.

2.3. Introduction to Sales Forecasting

According to Skjøtt-Larsen et al. (2007), the implementation of advanced demand forecasting systems can provide decisive results on consumption patterns and market trends. Statistical methods, such as time series models, are widely used to predict future demand based on historical data (Kotu & Deshpande, 2019).

In addition, machine learning and artificial intelligence techniques have become increasingly popular in demand forecasting due to their ability to handle large volumes of data and identify complex patterns (Zohdi et al., 2022). Chopra and Meindl (2019) point out that machine learning algorithms, such as neural networks and decision trees, can also improve the accuracy of demand forecasts.
Correlation analysis can identify relationships between sales and external factors, such as economic and climatic conditions. For example, a positive correlation between high temperatures and gin sales could indicate that warm weather boosts consumption of this drink (Hagström et al., 2019).
Models such as ARIMA (AutoRegressive Integrated Moving Average) and its seasonal extension, SARIMA (Seasonal ARIMA), are frequently used. These models allow for the modelling of both trend and seasonality in historical sales data. When external factors are incorporated into these models, it's used SARIMAX (Seasonal ARIMA with exogenous variables), making it fundamental for real-world applications where external influences play a significant role in sales behaviour (Hyndman & Athanasopoulos, 2018).

2.4. Forecasting models

Arima Model

The ARIMA (AutoRegressive Integrated Moving Average) model is one of the most commonly used time series models for sales forecasting, created by Box and Jenkins (1976). ARIMA models capture trends and noise in the data by combining three key components: AR (AutoRegressive), I (Integrated), and MA (Moving Average).

$$y_t = \mu + \sum_{j=1}^{p} \emptyset_j \left(y_{t-j-\mu}\right) + \sum_{j=1}^{p} \psi_j \varepsilon_{t-j} + \varepsilon_t \tag{1}$$

The AR part of ARIMA shows that the time series is regressed on its own past data. The MA part of ARIMA indicates that the forecast error is a linear combination of past respective errors. The I part of ARIMA shows that the data values have been replaced with differenced values of d order to obtain stationary data, which is the requirement of the ARIMA model approach (Kotu & Deshpande, 2019).
ARIMA is ideal for time series data that exhibit clear trends but lack strong seasonality. However, in many sales datasets, seasonality is prominent (e.g., holiday spikes, weekend peaks), which limits ARIMA's effectiveness. y_t is the value of the time series at time *t,* μ The mean (or constant term) of the time series, p The order of the autoregressive (AR) process, Ø The autoregressive (AR) coefficients for the *j,* the ψ_j is the moving average (MA) and the ε_t is the error term (or white noise) at time *t.*

Sarima Model

To account for seasonality, the SARIMA model extends ARIMA by adding seasonal components to the autoregressive and moving average terms. SARIMA is represented as SARIMA (*p,d,q*)(*P,D,Q*) *s*, where the parameters *p, d, q* represent the non-seasonal part and *P, D, Q* are the seasonal parameters, with s representing the length of the seasonal cycle, the equation (2) can be describe as

$$y_t = \mu + \sum_{j=1}^{p} \emptyset_j (y_{t-j} - \mu) + \sum_{j=1}^{q} \psi_j \varepsilon_{t-j} + \sum_{j=1}^{P} \emptyset_j (y_{t-j} - \mu) + \sum_{j=1}^{Q} \psi_j \varepsilon_{t-j} + \varepsilon_t \tag{2}$$

In sales forecasting, SARIMA is particularly effective for businesses that experience periodic sales fluctuations, such as holiday or back-to-school shopping periods. SARIMA captures both the trend and seasonality in sales, allowing businesses to plan for these seasonal variations more effectively.

SARIMA models have been used, for example, to forecast demand for consumer electronics, accounting for seasonal sales peaks during the holiday season (Ensafi et al., 2022). By capturing both long-term trends and recurring seasonal patterns, SARIMA helps retailers optimize their inventory and anticipate the imbalance between sell-in and sell-out.

Sarimax and Exogenous Variables

The SARIMAX (equation 3), model extends SARIMA by incorporating external variables that influence sales. These exogenous variables can include economic indicators, marketing efforts, or weather conditions.

The inclusion of external factors significantly improves forecast accuracy, particularly in industries where external events (e.g., promotions, holidays) play a key role in driving sales. In retail, for instance, incorporating promotional activity and economic conditions into SARIMAX models has been shown to improve forecasting accuracy by accounting for these non-seasonal fluctuations (Zhang et al., 2022).

$$y_t = \mu + \sum_{j=1}^{p} \Phi_j (y_{t-j} - \mu) + \sum_{j=1}^{q} \psi_j \epsilon_{t-j} + \sum_{J=1}^{P} \Phi_J (y_{t-Js} - \mu) + \sum_{J=1}^{Q} \Psi_J \epsilon_{t-Js} + \beta X_t + \epsilon_t \tag{3}$$

2.5. Challenges in Sales Forecasting Using Time Series Model

2.5.1. Outliers

Outlier detection has become an important part of time series analysis, as they can significantly deviate from most of the data, impacting the accuracy of the forecast models (Romanuke, 2022). They can be unusually high or low values that might arise due to errors in data collection, recording, or natural variability in the data. In time series analysis, outliers can distort statistical measures and negatively impact the accuracy of forecasting models (Vinutha et al., 2018).

Therefore, identifying and handling outliers is crucial in preprocessing time series data to ensure robust and reliable analysis. In the context of this study, outliers could represent exceptionally high or low sales figures that do not align with the general sales pattern.

One common method to detect outliers is by using Z-scores, which measure how many standard deviations a given data point is from the mean of the dataset (Altman & Bland, 1995). A Z-score is calculated as equation 4 where X is the data point, μ is the mean of the dataset, σ is the standard deviation of the dataset as seen in the equation below.

$$Z = \frac{(X - \mu)}{\sigma} \tag{4}$$

In a normal distribution, data points with Z-scores greater than 3 or less than -3 are typically considered outliers (Sheskin, 2004). Outliers detected using this method are often corrected or removed to avoid distorting the analysis, particularly when they result from errors or rare events that are not representative of the underlying trend. In this study, the outliers detected were transformed into null values and the interpolation was used to handle these missing values. The default method applied was linear interpolation, which was chosen for its simplicity and effectiveness in estimating values when the underlying trend between points is expected to be roughly linear (Burden & J. Douglas Faires, 2010).

In time series analysis and other fields of data science, interpolation is a method used to estimate unknown values that fall between known data points. When handling real-world datasets, it is common to encounter missing values or irregular measurements, often due to various reasons such as data collection errors, sensor failures, or communication issues. In such cases, interpolation becomes a valuable tool to fill in these gaps and allow for further analysis or modeling (Press et al., 2007).

Linear interpolation assumes that the values between two known points change at a constant rate, effectively estimating the unknown value by fitting a straight line between the surrounding data points (Greenbaum & Chartier, 2012). Equation 5 represents the formula of the linear interpolation, where x_1 and x_2 are the known data points, and y_1 and y_2 are their corresponding values. This method is effective when the data follows a relatively linear trend between the missing points (Burden & J. Douglas Faires, 2010).

$$y = y_1 + \frac{(x - x_1)}{(x_2 - x_1)} \times (y_2 - y_1) \tag{5}$$

By using interpolation and outlier detection techniques, the datasets were prepared for further analysis, including time series decomposition and forecasting, ensuring that missing values did not introduce bias or inconsistencies in the results. This approach aligns with best practices in data preprocessing, where the goal is to maintain data continuity while minimizing assumptions about unknown values.

2.5.2. Stationarity and Differencing

One of the key assumptions in time series models like ARIMA and SARIMA is that the data must be stationary (Wang et al., 2021). This means that the statistical properties (e.g., mean, variance) of the time series should not change over time. Most of the time, sales data are often non-stationary due to long-term trends and seasonal effects. Differencing is applied to make non-stationary data stationary by subtracting the previous observation from the current one (Hyndman & Athanasopoulos, 2018). However, over-differencing can lead to a loss of information, while under-differencing may leave residual trends that impact model performance. In sales forecasting, achieving the right level of differencing is crucial for model accuracy (Ihalainen, 2024). Applying the Augmented Dickey-Fuller (ADF) test, equation (6), can help determine whether the series is stationary and if differencing is required. The ADF test is an extended version of the Dickey-Fuller test, which was developed to test for the presence of a unit root in time series data (Dickey & Fuller, 1979). A unit root indicates that the series is non-stationary. The ADF test improves upon the original by allowing for higher-order autoregressive processes in the time series, making it more applicable to real-world data.

The null hypothesis ($H0$) of the ADF test states that the time series has a unit root (i.e., the series is non-stationary), while the alternative hypothesis ($H1$) suggests that the series is stationary. If the p-value from the ADF test is lower than a chosen significance level (typically 0.05), the null hypothesis is rejected and concludes that the series is stationary.

$$\Delta y_t = \alpha + \beta t + \gamma y_{t-1} + \delta \sum_{i=1}^{r} \Delta y_{t-1} + \epsilon_t \tag{6}$$

In sales forecasting, especially with models like SARIMA and SARIMAX, the ADF test is crucial for determining whether differencing is required. Differencing transforms a non-stationary series into a stationary one, which is necessary for ARIMA-based models to produce accurate forecasts. If the test indicates non-stationarity, differencing is applied until the series becomes stationary. Once stationarity is achieved, the ARIMA or SARIMA model can be fitted to the data (Hyndman & Athanasopoulos, 2018).

An example of the ADF test applied in sales forecasting comes from the retail industry, where monthly sales data were analyzed to predict future demand for consumer goods. In the study by Ferreira et al. (2016), the sales data showed strong seasonal patterns. The ADF test was applied to determine the stationarity of the data. Initially, the test indicated non-stationarity, and a first differencing was applied to achieve stationarity. After stationarity was confirmed, the SARIMA model was fitted, resulting in accurate forecasts for seasonal sales periods, such as Black Friday and Christmas.

2.5.3. Parameter Selection in SARIMA/SARIMAX Models

SARIMA and SARIMAX models extend the ARIMA framework by adding seasonal components, making them appropriate for datasets with recurring patterns, such as monthly sales spikes during holiday seasons or quarterly financial reports. The parameters are typically divided into two categories: non-seasonal and seasonal. Non-seasonal parameters*: p:* The number of Lag observations included in the model (AutoRegressive or AR terms). This represents how many past observations should influence the current observation, *d*: The degree of differencing. This parameter helps to remove trends and make the data stationary. The data is differenced *d* times to achieve stationarity, *q:* the size of the moving average window (Moving Average or MA terms). This refers to the number of lagged forecast errors included in the model. The season parameters, *P:* The number of seasonal autoregressive (SAR) terms, *D:* The degree of seasonal differencing. This parameter is similar to *d*, but it applies to seasonal trends. *Q:* The number of seasonal moving average (SMA) terms and the *s:* The length of the seasonal cycle (e.g., 12 for monthly data with yearly seasonality, 4 for quarterly data).

Approaches to Parameter Selection

Different approaches are used for parameter selection, from manual inspection of time series plots to automated methods such as grid search, stepwise selection, and cross-validation. Each method offers distinct advantages and is suitable for different types of datasets. This section explores several common approaches to parameter selection in SARIMA and SARIMAX models, including manual techniques based on autocorrelation analysis, systematic grid search, stepwise AIC-based selection, and validation through cross-validation techniques (Hyndman & Athanasopoulos, 2018).

One of the traditional methods for parameter selection in ARIMA and SARIMA models is using AutoCorrelation Function (ACF) and Partial AutoCorrelation Function (PACF) plots. These plots help identify the appropriate values for the autoregressive (***p***) and moving average (***q***) components, by counting the significative correlation in the correlogram.

The complexity of parameter selection increases with the inclusion of seasonal components and exogenous variables. Researchers have explored automated approaches, such as stepwise AIC-based searches, to streamline parameter selection while maintaining forecast accuracy.

A more automated and systematic approach to parameter selection is through grid search. This involves testing a range of different values for (*p,d,q*)(*P,D,Q*) *s*, and evaluating the performance of each model using AIC (Akaike Information Criterion) or BIC (Bayesian Information Criterion) (Hyndman & Athanasopoulos, 2018).

Studies like (Zhang & Qi, 2005) used grid search to forecast sales with ARIMA and SARIMA models. They examined the best model time series with both seasonal and trend components.

2.6. Model selection and AIC, RSME and MAE in Time Series Forecasting

Model selection is a critical step in time series forecasting. In SARIMA and SARIMAX models, the Akaike Information Criterion (AIC) is one of the most widely used techniques for achieving this balance Burnham & Anderson (2004).

$$AIC = 2k - 2\ln(L) \tag{7}$$

AIC measures the trade-off between the complexity of the model and how well the model fits the data, where *k* represents the number of parameters in the model, and ***L*** is the likelihood of the model given the data as seen on equation (7). The goal is to minimize AIC, choosing a model that balances fit with simplicity. A lower AIC indicates a better model.

In time series models like ARIMA, SARIMA, and SARIMAX, numerous parameters need to be selected, such as the autoregressive (AR), differencing (I), and moving average (MA) components, as well as seasonal terms. With so many possible configurations, AIC becomes an invaluable tool for determining which configuration best captures the underlying patterns in the data while avoiding overfitting (Milenković et al., 2016).

Adding to AIC, another key metric used to evaluate model performance is the Root Mean Squared Error (RMSE) equation (9) and the Mean Absolute Error (MAE) equation (8), these metrics show how far off a model’s predictions are from the actual values. It calculates the average difference between what the model predicts and what actually happens (Chai & Draxler, 2014).

$$MAE = \frac{1}{n}\sum_{t=1}^{n}|y_t - \hat{y}_t| \tag{8}$$

$$RMSE = \sqrt{\frac{1}{n}\sum_{t=1}^{n}(y_t - \hat{y}_t)^2} \tag{9}$$

RMSE calculates the average difference between what the model predicts and what actually happens. Lower value of this metric means that the model's predictions are closer to the actual values, indicating better accuracy. While MAE It is calculated as the average of the absolute differences between the actual observed values and the predicted values, a lower MAE indicates a more accurate model, as it suggests smaller average errors in the forecasts. The representation of the actual observed values is represented by the y_t, the $\hat{y}_t$ are the values predicted by the model and finally n is the number of observations.

2.7. ARIMA and SARIMA in Sales Forecasting

The ARIMA model has become a staple for time series forecasting, particularly in sales contexts. It is especially effective when sales data exhibit strong autocorrelations and trends. The SARIMA model, which adds seasonal components to ARIMA, is a powerful tool for sales forecasting when seasonality plays a significant role in demand, such as retail sales during holiday seasons (Makridakis et al., 1997).

In retail, Taylor et al. (2008) demonstrated the effectiveness of SARIMA models in forecasting intraday call center arrivals, such as hourly patterns in short-term demand forecasting. This approach can be extended to retail sales forecasting, where it is vital to account for cyclical trends, such as monthly or quarterly sales variations, to improve the accuracy of predictions and inventory management. Forecasting future sales involves understanding both the internal patterns in historical sales data (such as trends, cycles, and seasonality) and the external factors that might influence future sales. Time series models like SARIMA and SARIMAX are particularly effective in capturing these dynamics. The application of time series models in sales forecasting has been well-documented across industries, ranging from retail to manufacturing.

2.8. External Factors

Accurate sales forecasting is crucial for effective business planning and decision-making. Traditionally, sales forecasts have heavily relied on historical sales data and internal business factors such as inventory levels and marketing efforts. However, recent studies emphasize the significance of integrating external factors to enhance the precision of these forecasts (Fildes et al., 2022).

Economic Indicators

One of the most impactful external factors is the set of macroeconomic indicators, such as Gross Domestic Product (GDP), unemployment rates, and consumer confidence indices. These indicators provide a broader context in which sales occur, allowing companies to predict fluctuations due to changes in the overall economy. Fildes and Hastings (1994) demonstrated that incorporating economic indicators significantly improves the accuracy of demand forecasts, particularly in volatile markets.

Weather Conditions

Meteorological conditions have been identified as another critical external factor influencing sales in industries such as retail and agriculture. Studies by Rose and Dolega (2021) illustrate that weather patterns can lead to variations in consumer behavior; warmer weather might increase the sales of summer-related products, while colder temperatures could increase the demand for hot drinks and fewer ice drinks, which may affect your average price and number of monthly transactions.

The Direct Impact of Tourism on Beverage Consumption

Tourism in a country directly influences beverage sales, as tourists often dine out, visit bars, and purchase beverages during their travels. The influx of tourists can lead to substantial increases in demand for both alcoholic and non-alcoholic drinks. According to studies by Lim (2006) and Song and Li (2008), businesses that fail to account for these surges may experience stockouts or overstock during off-peak seasons. By integrating tourism data, such as the number of tourist arrivals or hotel occupancy rates, into sales forecasts, businesses can better align their inventory levels with actual demand. Incorporating tourism as an external factor in sales forecasting models allows for more accurate and responsive predictions (Song et al., 2008).

Granger Causality Test

The Granger causality test, introduced by Granger (1969), is a statistical hypothesis test for determining whether a time series can help to predict another one. This test is grounded in the notion of temporal precedence and attempts to evaluate whether past values of one variable provide statistically significant information about the future values of another (Breitung & Hamilton, 1995). Conducted the causality to check whether the historical values of specific variables (e.g., Unemployment Percentage, GDP, Number of Sleeps, Temperature, and Precipitation) can statistically predict future values of sales.

2.9. The Role of Exogenous Variables in Sales Forecasting

Although ARIMA and SARIMA models rely solely on the historical values of the target variable, real-world sales are often influenced by external factors, such as promotional campaigns, economic conditions, and weather patterns. This is where the SARIMAX model becomes particularly useful. By including exogenous variables, SARIMAX improves the accuracy of forecasts by accounting for external factors that can influence sales (Zhang et al. 2022).

Ferreira et al. (2016) showed that incorporating variables such as holiday periods and advertising campaigns significantly improved the accuracy of demand forecasts in the retail industry. Similarly, in a study on fast-moving consumer goods, Taylor and Letham (2017) found that using SARIMAX models to integrate exogenous variables such as economic conditions and market trends provided more reliable sales forecasts.

In sectors like energy and utilities, Zhang et al. (2022) used SARIMAX models to forecast energy consumption based on weather conditions (e.g., temperature and humidity), further demonstrating the effectiveness of SARIMAX in scenarios where external factors are known to affect demand.

2.10. Advances and Hybrid Approaches in Time Series Sales Forecasting

As businesses continue to explore more sophisticated forecasting techniques, traditional models like SARIMA and ARIMA face limitations in handling complex and irregular patterns, such as multiple seasonalities and external events (Hyndman & Athanasopoulos, 2018). This has led to the rise of hybrid approaches that combine traditional time series models with machine learning and more advanced models such as Facebook Prophet. Prophet, developed by Facebook, is a robust time series model specifically designed to handle real-world data complexities, including multiple seasonality and holiday effects, with minimal parameter tuning (Taylor & Letham, 2017). Prophet models time series data as an additive model, where components such as trend, seasonality, and holidays are added together to generate forecasts. The model is flexible enough to handle missing data, outliers, and shifts in trend, which often occur in sales data. The key components of the Prophet model are Trend and Seasonality. Trend captures the long-term increase or decrease in the time series, while seasonality handles repeating patterns such as weekly, monthly, or yearly cycles. One of Prophet's key advantages, particularly in sales forecasting, is its ability to incorporate external (exogenous) variables into the forecasting model.

Models like SARIMAX are designed to handle these external variables by incorporating them directly into the forecasting equation. However, setting up these models can be complex, and they require substantial parameter tuning to ensure that the model adequately accounts for the influence of external factors. Prophet simplifies this process by allowing users to easily add external variables as regressors into the model. These regressors are treated as additional covariates that can affect the trend, and the model automatically estimates their impact on the forecasted values. This makes Prophet particularly powerful for businesses where external events play a critical role in sales outcomes.

Research Gap

The identified articles explored in this research address, particularly: topics concerning sales forecasting, the utilization of external variables, challenges in demand forecasting for specific products the integration of AI and ML technologies in the food and beverage industry. The literature reviewed reveals a research gap in achieving sell-in/sell-out equilibrium in the spirits beverage retail sector and the study of each sector. Although it was possible to comprehensively analyze the existing studies, a noticeable research gap persists in understanding and addressing the dynamics between sell-in and sell-out strategies within this topic. Therefore, the aim of this study is to focus on forecasting specific cases of sales within the spirits market, implementing two distinct forecasting models based on the influence of external factors, by making this is possible to overcome this gap and to understand and predict demand patterns in spirits beverages sales on the on-trade channel, providing insights for better decision-making in this sector.

Chapter 3

Methodology

Choosing the methodology is an important step for conducting quality studies in any research field, this research used the CRISP-DM (Cross-Industry Standard Process for Data Mining) methodology due to its structured, flexible, and iterative nature throughout its life cycle.

Developed in 1996, this methodology is widely used for data mining projects, it provides a structured, well-defined approach applicable across various domains (Wirth & Hipp, 2000). Its flexibility allows for specific adaptations depending on the data type and study contexts. In this case, analyzing beverage sales in the sector of on-trade of the sell-in distribution method, understanding sales drivers, and accurately forecasting sales, ultimately aiding in efficient inventory management and consumer satisfaction.

The initial focus on understanding the business ensures the data analysis aligns closely with the objectives, enabling meaningful insights and business process improvements. This methodology divides the data process into six phases ensuring an organized approach to the main goal: business understanding, data understanding, data preparation, modelling, evaluation and implementation.

3.1. Business Understanding

Sales forecasting, which involves predicting revenue within a specific period, has always been a vital factor for businesses to succeed. Forecasts help a business attain revenue efficiency by offering insight into the likely behavior of valuable customers (Hall, 2020). During the business understanding phase, the definition of the project's objectives and requirements was elaborated from a business perspective. In this phase, according to Shearer (2000), it is essential to identify the main stakeholders, understand the business problems, and formulate the research questions that the project aims to answer. To achieve this, several meetings were held with the point of contact (POC) from the company, during which the project's goals and the company's specific needs were discussed. Furthermore, it was conducted a visit to the company’s headquarters to gain a deeper understanding of its internal operations and daily activities. During this visit, presentations were made by the company, providing us with a detailed insight into their business, which allowed us to align the research with the company's operational needs and expectations. These interactions were critical for formulating an action plan that was both accurate and specified for the company's needs, ensuring that the project met its key requirements and strategic goals. The research questions to be addressed include:

1. What are the main external factors influencing the on-trade channel in the beverage spirits industry?
2. What prediction models can be made for different types of drinks?
3. How can the discrepancy between sell-in and sell-out be mitigated?

3.2. Data understanding

The provided dataset contains information on monthly sales of different spirits beverages, categorized by group code and bottle size from the on-trade channel from the company's internal sales record, collected from April 2013 to March 2024.

The original dataset contains 27 records (rows) and 134 columns. The first two columns represent each group code and size of a beverage, and the rest of the columns cover the sales over the last 11 years, each column represents the sales on a specific month of a particular year, e.g., APR 2013. In Table 3.1, it is possible to see a representation of each variable with the meaning, type, and example of each variable. Each sale represents a unit of sale of 9L cases of each type of beverage. The columns "Group Code" and "Bottle Size" are columns with categorical variables. The "Group Code" column contains the beverage type/brand, which is a nominal categorical variable. This variable identifies the specific type of beverage without any specific rank. For instance, the name of the brand beverage represents a specific group code in the dataset. The "Bottle Size" column specifies the size of the beverage bottle, and it is an ordinal categorical variable. This variable not only categorizes the products but also provides an inherent order based on the size of the bottle, serving as a unique identifier for each product variant and helping distinguish between different products within the same group. Examples include " 100 CL", "75 CL", and "6 CL".

Table 3.1 - Types of Variables present on the dataset

Column	Meaning	Type of Variable	Example
Group Code	Beverage group code	Nominal categorical	Group Code Asti Martini
Bottle Size	Size of the bottle	Ordinal categorical	75 CL
APR 2013	Monthly sales for April 2013	Continuous numerical	100.0

Data preparation

Data preparation is an important stage in the process of analyzing data and developing machine learning models. Data preparation included data cleaning, merging the different data sets from external factors, and normalizing and transforming data to achieve the desired results. Each performed step is imperative to ensure the data are consistent and ready to enter the modeling stage and to pursue the best results possible.

Handling missing values

The original dataset contained several missing values (NaN), which could compromise the integrity of the analysis. To deal with this, all missing values were replaced with zero. This approach assumes that the absence of data represents the absence of sales in that specific period. Replacing missing values is a common practice to avoid problems during modeling, ensuring all algorithms can process the data without interruption. According to Han et al. (2011), the imputation of values is essential to maintain data consistency.

Date Conversion

The 'Month_Year' column was split into 'Month' and 'Year', and the new columns were converted into a standard date-time format. This step is crucial to enable aggregation and a future temporal analysis. The correct formatting of dates is essential for the accuracy of forecasts (Taylor & Letham, 2017).
To facilitate the analysis and to make the descriptive part easier, the date columns were transformed into rows, creating a new "Sales" column. This approach, known as melting, is useful for converting data from wide to long format, making it more accurate for time series analysis. A new dataset was created that included a total of 3565 rows and 7 columns, encapsulating various attributes related to the sales data.
The new dataset includes now the columns ‘group code’, ‘bottle size’, ‘Month_Year’, ‘Sales’, ‘Month’, ‘Year’ and ‘Date’, The seventh column represents the data and specify the first day of the respective month and year in, helping for conducting time series analysis and understanding temporal patterns in sales data.

Each row represents the sales information for a particular product group and bottle size (SKU), within a specific month and year. These values are continuous and can take on any value within a specified range, providing precise measurements of sales performance. The categorical variables provide qualitative insights into the different SKUs, while the numerical variables allow for a detailed quantitative analysis of monthly sales trends.

3.3. Descriptive Statistics

One key step in the data analysis process involved identifying the top-selling SKUs and their specific attributes, such as bottle size, to gain insights into consumer preferences and market trends. This information is vital for making informed strategic decisions for product offerings, inventory management, and marketing strategies.

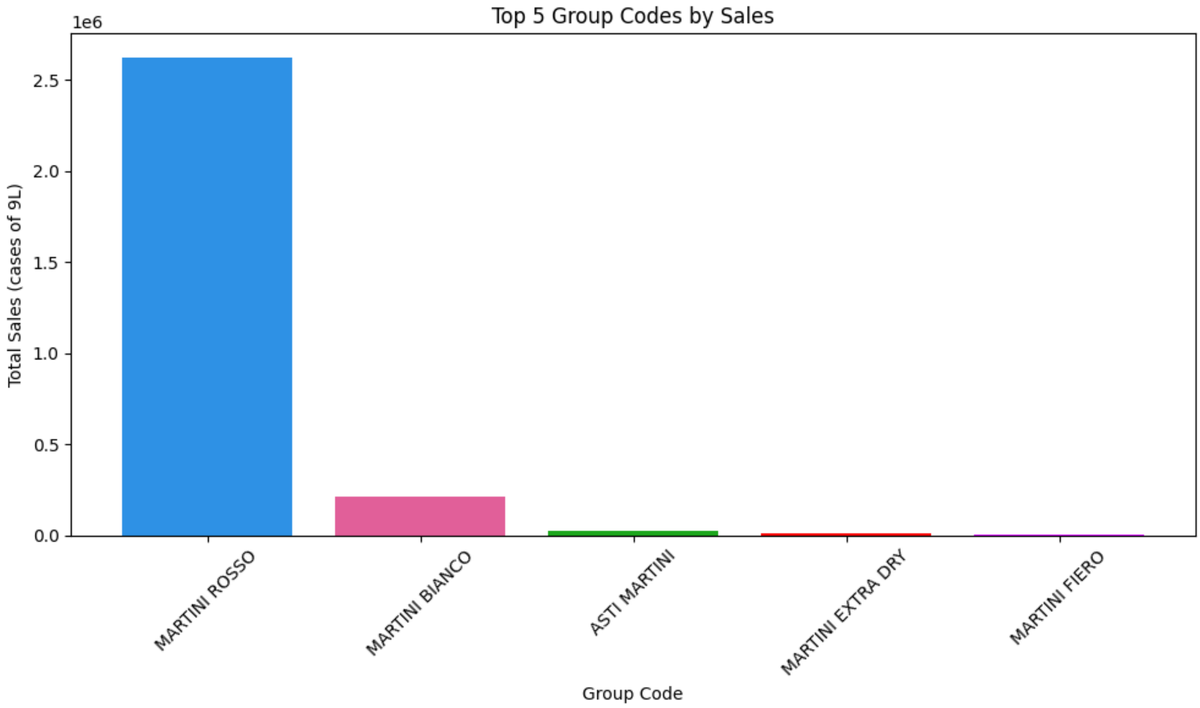

Figure 3.1 Total Sales of the TOP 5 Group Code (in Millions of 9L Cases)

The top five group codes by total sales, Figure 3.1, reveal the most successful products during the years of the dataset. Leading the sales with an impressive total sales figure of over 2.6 million sales is represented the *Martini Rosso* group code. This is followed by group code *Martini Bianco*, which generated around 213,000 in sales, and finally, group code *Asti Martini* in third place.

On the other end of the spectrum, the analysis of the bottom five group codes by sales, Figure 1 of the Appendix, sheds light on the products struggling to gain traction. *Martini Sparkling Rose*, *Martini Prosecco*, and *Gran Lusso* are among the lowest, with *Martini Sparkling Rose* posting a mere 6.00 in sales. *Martini Prosecco* and *Gran Lusso* are not faring much better, with sales of 17.58 and 123.99, respectively. This stark contrast in sales performance highlights areas were strategic adjustments, such as marketing efforts or product improvements, could be beneficial.

According to Figure 3.1, it is possible to highlight the overwhelming dominance of the group code *Martini Rosso*, having the highest percentage of sales during the time frame. *Group code Martini Bianco* also showed moderate performance, having roughly 7% of the sales during the same time frame. The *Group code Asti Martini* occupies niche markets with specific consumer appeal.

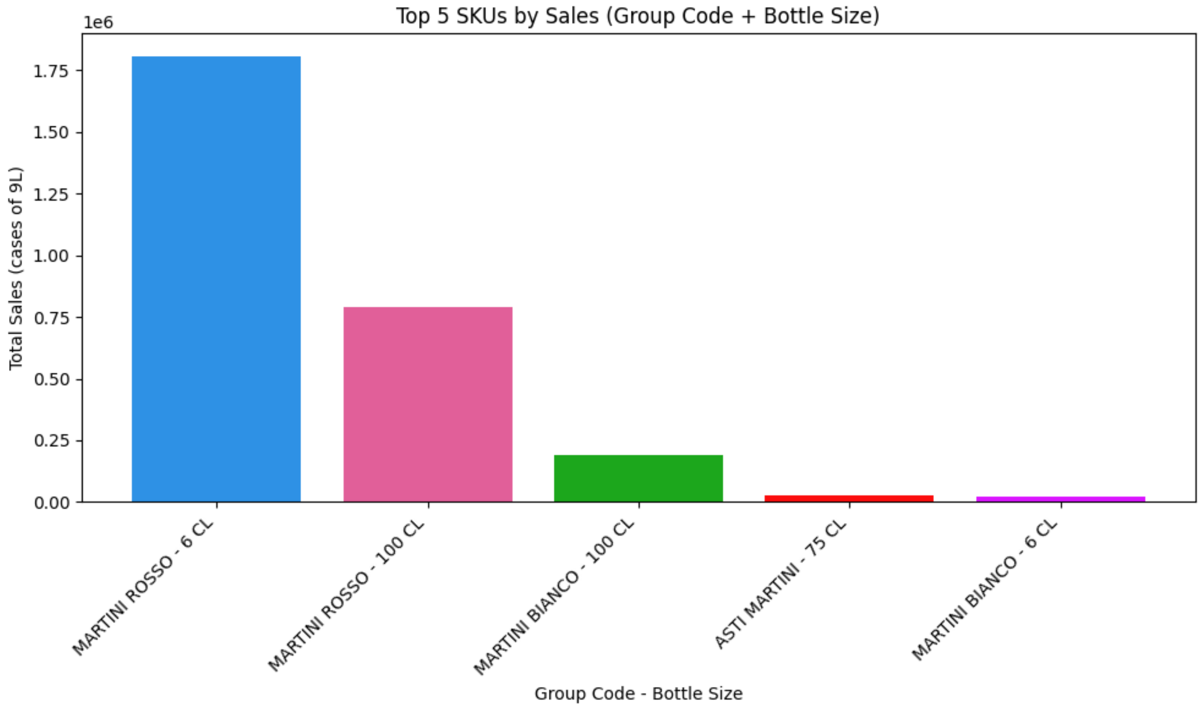

Figure 3.2 - Total Sales of the Top 5 SKUs (Group Code + Bottle Size) in Millions of 9L Cases

Breaking down the data by group code and bottle size, Figure 3.2 provides a more detailed view of sales trends. Among the top-performing combinations, the drink *Martini Rosso* 6CL and the drink *Martini Rosso* 100CL, obtained sales figures of 1,808,285.29 million and 791,658.28 respectively. This indicates that consumers appreciate more the group code *Martini* Rosso, followed by the drink *Martini Bianco* 100CL with 188,564.27, *Asti Martini* 75CL with 25,771.5 and *Martini Bianco* 6CL 20,575.33 sales.

According to figure 35 from appendix, the descriptive analysis of the top 5 SKUs revealed significant variations in sales performance. The SKU with less sales, Martini Bianco (6 Cl) showed a stable pattern with a mean of 155.9 sales and a lower standard deviation of 121.7. The SKU Asti Martini 75CL exhibited an average sales volume of 195.2 units with a maximum of 2,255, showcasing high variability (standard deviation of 378.8), suggesting fluctuating demand. The Martini Bianco (100 Cl) had an average of 1,428.5 sales, with a peak of 3,676.7 and substantial variability (standard deviation of 878.7), reflecting consistent and more sales but occasionally irregular sales. Entering in the group code of Martini Rosso, the SKU Martini Rosso 100CL stood out with an average sales volume of 5,997.4 sales and a maximum of 15,859.3, demonstrating considerable variability (standard deviation of 3,248.4) and finally the Martini Rosso (6 Cl) dominated with a mean of 13,699.1 sales and a peak of 32,230.5, emphasizing its significant contribution to overall sales and its highly variable nature (standard deviation of 6,999.0), these results highlight the diverse sales dynamics across the top % SKUs.

3.4. Analysis of Seasonal Trends

From the Figure 3.3, it is possible to observe seasonality patterns and fluctuations in sales during the dataset's timeline. These components are important for stock planning and marketing campaigns. The line graph illustrates sales performance over eleven years, starting in April 2013 and ending in March 2024.

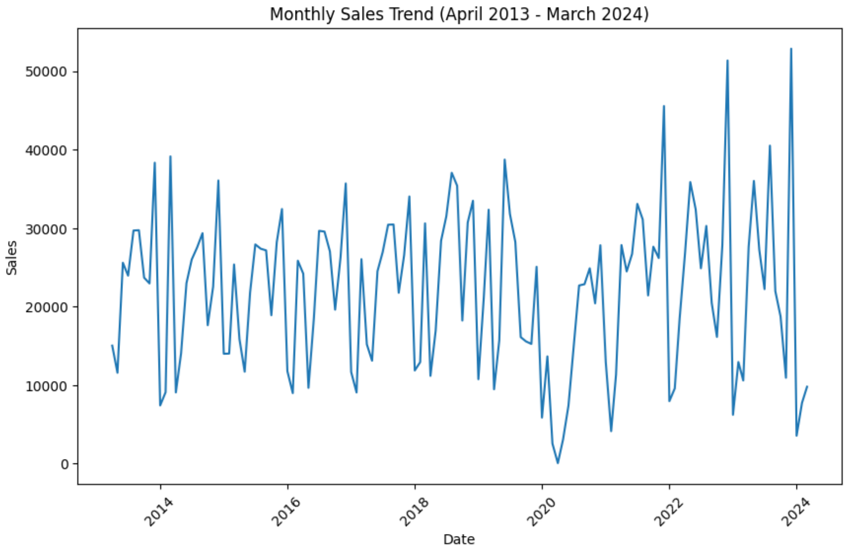

Figure 3.3 - Monthly Sales Trend from April 2013 to March 2024

From 2013 to 2016, the sales trend showed frequent sales peaks in December. During the time frame, the sales values generally range between 10,000 and 30,000, with occasional spikes indicating months of higher sales performance. Between 2017 and 2020, the sales follow a similar pattern as described for the previous years. On the year of 2020, it's shown to be the lowest year on the dataset, this can be justified by the economic shock caused by lockdowns and the temporary closure of businesses during the early months of the COVID-19 pandemic, this effect can be observed in the sales data for 2020, where many industries reported a substantial reduction in revenue, directly attributable to the restrictions imposed to mitigate the spread of the virus (Bartik et al., 2020). From 2021 onwards, the data shows increased volatility. There are more pronounced peaks where sales exceed 40,000 and reach above 50,000 units in some months. In 2022 and 2023, the data show a strong recovery in sales, likely drove by consumer demand and government stimulus efforts that injected liquidity into economies to support recovery (Chetty et al., 2020).

Figure 3.4 provides a clear understanding of the seasonal variations and trends in sales over these years, each bar signifies the sales volume for the month with the highest sales in that particular year.

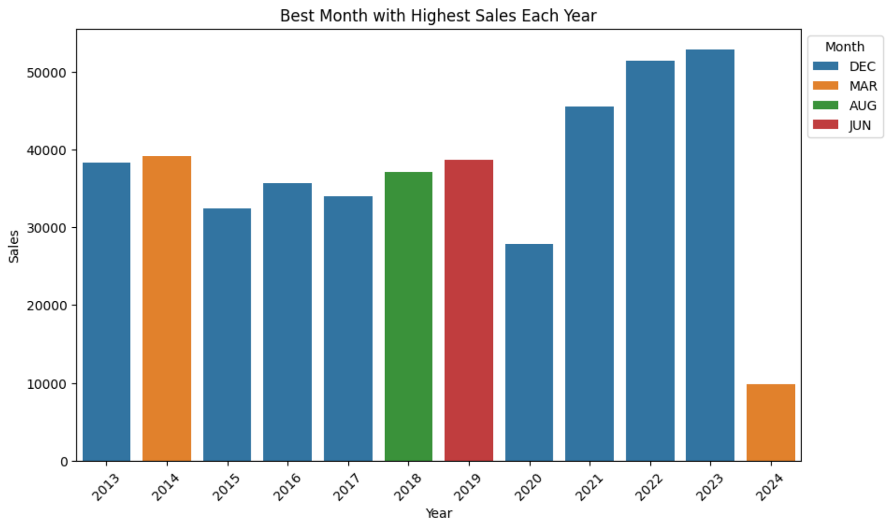

Figure 3.4 - Best Month with Highest Sales Each Year

It is possible to detect a prevalence of December as the peak sales month, occurring in eight of the twelve analyzed years (2013, 2015, 2016, 2017, 2020, 2021, 2022, and 2023). This suggests a strong seasonal influence likely driven by holiday shopping behaviors and adding to the fact that the annual price increase takes place in January, coinciding with the tax increase (IABA - *Imposto sobre o álcool e as bebidas alcoólicas*) imposed by the government. This leads to a significant increase in demand in December, as customers anticipate the increase of the price on the various products. The variations in peak months highlight the importance of understanding seasonal patterns, the external factors and adapting sales strategies to maximize performance throughout the year.

Notably, 2022 and 2023 saw exceptionally high sales figures in December, surpassing 50,000 units. This could be attributed to successful sales strategies, promotional activities, broader economic conditions supporting higher consumer spending during these months, or even the final stage of Covid-19.

3.5. External Variables

Overnight stays

The tourism data was sourced from Instituto Nacional de Estatistica (INE), this dataset tracks the number of overnight stays by tourists in Portugal. This data will be integrated into the forecasting model as an exogenous variable to capture the seasonal patterns and peaks in sales driven by tourism fluctuations. This variable will help the model predict sales more accurately during periods of high tourist activity. The data on overnight stays accommodation establishments was initially provided with a monthly frequency, showing the total number of stays per month, it was necessary to convert the textual dates into a standardized format and adjust the column names, this transformation ensured data consistency and simplified its use in time series-based models and for further analysis.

GDP Data

The GDP data was also sourced from the Instituto Nacional de Estatistica (INE). The dataset provides detailed information on the country's economic performance over time, which tracks Portugal's economic performance on a trimester basis. The dataset contains information on the overall economic growth rate and sectoral contributions to GDP. By including GDP as an exogenous variable, the model can adjust forecasts to account for economic trends that influence consumption behavior. The initial dataset presents the quarter name and the corresponding aggregate value for the three-month period. To adapt the dataset to analytical and modeling needs, a transformation was performed to obtain monthly GDP values. This transformation involved distributing the quarterly values evenly across the three corresponding months and each quarterly value was replicated for the months within the respective period, preserving the coherence of the quarterly totals. This transformation is essential for predictive models that require time series at a monthly frequency, such as those used in the present study.

Unemployment Data

The unemployment data was collected from BPstat, Banco de Portugal Eurosistema, tracks the unemployment rate in Portugal on a monthly basis. This dataset will be used in the forecasting model to account for the effects of labor market conditions on sales.

Including unemployment as an exogenous variable will help capture this relationship and improve the accuracy of sales forecasts under varying economic conditions.

These datasets will be pre-processed (e.g., normalized, aligned by time period, months) and then included in the forecasting model as exogenous inputs, enhancing the model's ability to predict future sales based on fluctuations in tourism, weather, economic growth, and employment.

Data Integration and Merging of Exogenous Variables

All of the external variables were merged into a new dataset by date. To ensure consistency with the main sales dataset, a series of preprocessing steps were applied to the exogenous variables: match of the exogenous dataset to the timeframe of the sales data, the original date column was reformatted, and the exogenous dataset was indexed by this new date range to ensure that the time periods were aligned across both datasets. The original date column was dropped to avoid redundancy, and the "Date" field was set as the index for future merging purposes. The merging process involved concatenating the exogenous variables with the sales data along the date index. By combining these datasets, the forecasting model accessed the internal sales values and key external drivers, such as unemployment rates, GDP and tourism activity. The merged dataset was then saved as a new data set, which was used for model training.

3.6. Time Series Decomposition

Time series decomposition is an also an important method for analyzing the patterns in a dataset collected over time, this analysis is performed on sales data, providing insights into the sales trend and seasonality.

On the second plot illustrated in the Figure 3 of the appendix displays the trend component, which represents the long-term progression of the data: initial stability, followed by a sharp decline around 2019 and staying significantly low during these years until the beginning of 2021. The sharp decline around the year 2019 could be attributed to external economic factors, market changes, or other significant events, including the impact of the COVID-19 pandemic. While the recovery phase post-2021 and subsequent gradual decline suggest shifts in market dynamics or consumer behavior (Ibn-Mohammed, 2021).

The third plot also from the Figure 3 of the appendix illustrates the seasonal component, capturing a consistent repeating pattern, suggesting that sales experience periodic highs and lows at regular intervals. This indicates some seasonal effects that might be due to factors such as holidays, weather changes, or other factors, and all of these effects can drastically impact the selling market's performance.

The last plot represents the residual component, the remainder after removing the trend and seasonal components from the original series. The residuals represent the irregular or random variations in the data. This component encompasses the noise and anomalies that cannot be explained by the trend or seasonality ((Box & Al, 2015).

The additive decomposition model was chosen for its simplicity and effectiveness in separating the time series into distinct components. This approach allows for a clear interpretation of trends and seasonal effects, which are critical for understanding sales dynamics in the spirits industry. After doing the time series decomposition for the general dataset, was created new datasets for the five top SKU for deeper study and to handle the outliers for each SKU, Figures 4, 5, 6, 7 and 8 in the Appendix.

Understanding and Handling Outliers in the Dataset

The time series data of each top SKU was decomposed in separated dataset for each SKU, and to identify outliers was focused on the residuals of each one, as they provide insight into whether certain data points deviate from the expected behavior after accounting for trend and seasonality. After calculating the Z-scores for the residuals, data points with Z-scores outside the range of -3 to 3 were flagged as outliers. This approach ensured that it was possible to detect points that deviated from the expected data pattern.

Figure 9 in the Appendix, shows the significant outliers detected in each dataset, along with their corresponding dates and residual values. After detecting the outliers, they were transformed into NaN (Not a Number) values and then was used linear interpolation to estimate and fill these missing values.

Splitting Data set

An essential aspect of developing robust and accurate forecasting models is appropriately handling data, particularly splitting datasets into training and testing sets before any analysis, including decomposition. The most widely used method is the 80/20 split, where 80% of the data is used for training the model, and 20% is held back for testing (Joseph, 2022). This methodology implemented two different train-test splits to ensure the robustness of the results, namely 90%, 95% to training and 10%, 5% to test. By using multiple train-test splits, was ensured that the forecasting model is evaluated under different conditions and is robust to variations in the data used for training. This evaluation method is important in determining the reliability and accuracy of time series models.

3.7. Stationary

The Augmented Dickey-Fuller (ADF) test was used to determine whether a time series has a unit root (that is, non-stationary) or is stationary. The ADF test has the following null hypothesis (H0): The time series has a unit root (i.e., it is non-stationary) and the alternative hypothesis (H1): The time series does not have a unit root (i.e., it is stationary).

If the result of the ADF Statistic is a negative number and the more negative it is, the stronger the rejection of the null hypothesis is that there is a unit root (the series is non-stationary). Otherwise, a low p-value (typically less than 0.05) indicates that the null hypothesis can be rejected, suggesting that the series is stationary.

To address non-stationarity, differencing was used, transforming the time series data by subtracting the previous observation from the current one. This process, known as first-order differencing, can be extended to second-order differencing if necessary. The differenced series is then examined to ensure it no longer exhibits trends or changing variances, making it suitable for further analysis. Following differencing, it was confirmed that the series had achieved stationarity. For this, the ADF was repeated.

Granger Causality Analysis

In this context, it was evaluated if external economic and tourism-related factors can be used to predict the sales of different product lines. A significant p-value (typically less than 0.05) indicates that the external variable Granger-causes the sales time series at a specific Lag, meaning the external variable contains information that can help forecast future sales of the top 5 SKU.

For each external variable, it was considered lags ranging from 1 to 12 months. This allows us to examine both short-term and long-term predictive relationships between external factors and sales.

For each external variable and each lag, the null hypothesis of the Granger causality test was that the external variable does not Granger-cause sales. The p-values from the Granger causality tests were used to determine the significance of the results. If the p-value is less than 0.05, the null hypothesis is rejected, meaning that the external variable Granger-causes the sales series at that specific lag.

Heat maps were created showing the p-values of the Granger causality tests for each product line across different lags. Each row in the heatmap represents one external variable, while each column represents a lag (from 1 to 12 months). The color gradient in the heatmap indicates the level of significance, with darker blue areas representing lower p-values (indicating stronger evidence of Granger causality) and red areas representing higher p-values (indicating no Granger causality). For each Granger causality test, the following hypotheses were tested: Null Hypothesis (H0): The external variable (e.g., unemployment rate) does not Granger-cause sales. Alternative Hypothesis (H1): The external variable does Granger-cause sales.

3.8. Modelling Phase

The SARIMAX (Seasonal AutoRegressive Integrated Moving Average with eXogenous variables) model is used to capture the dependencies between the time series of sales and the external variable overnight stays. SARIMAX is well-suited for our case due to its ability to incorporate seasonality and exogenous variables. Prophet, on the other hand, is an additive time series model developed by Facebook that is designed to handle complex seasonality, trends, offering flexibility and ease of interpretation.

Forecasting Selection

The primary models used in this analysis are the SARIMAX and Prophet model, SARIMAX builds on the ARIMA framework by incorporating seasonality (SARIMA) and exogenous variables and the choice of SARIMAX is driven by the need to account for both seasonality in the sales data and the influence of external factors.

The model selection of SARIMAX is performed by evaluating different parameter configurations in SARIMAX, to assess the performance of the model under different parameter configurations, AIC was used to compare model fits, penalizing overly complex models. Lower AIC values indicate better model fits, and the RMSE was used to measure the difference between the actual and predicted sales values, providing insight into forecast accuracy. Grid searches were created over a range of ARIMA and seasonal orders to identify the optimal configuration that minimizes AIC and RMSE. Prophet model optimization was performed through iterative tuning of the seasonal, trend, and holiday components. The goal for both models was to find the optimal configuration that best fits the data while maintaining high forecast accuracy. RMSE was used as a primary metric to measure the accuracy of the sales forecasts by this model.

Forecasting implementation

The SARIMAX model is trained using the historical sales data for all the 5 SKU datasets as the dependent variable, and the exogenous variable as an external input. The parameter space for the ARIMA components (*p, d, q*) and the seasonal components (*P, D, Q*) is defined as p, d, q: interval from 0 to 2, P, D, Q and 0 to 1 (seasonal components), seasonal Period was considered 12 months, to capture the yearly seasonality. The model's performance is evaluated based on the AIC and RMSE for each parameter configuration. The best model for each split (90-10 and 95-5) is selected based on the RMSE and its corresponding AIC.

The Prophet model is trained using historical sales data for the 5 SKU datasets, with Overnight stays included as an external regressor. The training process is carried out for both 90-10 and 95-5 splits to assess the model's performance on different data partitions. The seasonal period is set to monthly frequency (freq='MS') to capture yearly seasonality and trends in the data. The Prophet model is chosen for its ability to handle missing data and external regressors with high interpretability.

Grid Search for Hyperparameter Optimization for SARIMAX

Hyperparameter tuning is conducted via grid search, systematically testing combinations of the ARIMA and seasonal orders. The search space is intentionally kept manageable to avoid overfitting and ensure efficient computation.

Was done cross-validation by splitting the dataset into different training and testing sets (90-10 and 95-5). This approach ensures that the model's performance is evaluated across different data distributions, helping to confirm the model's robustness and generalization capability.

In each case, the model is fitted on the training data and evaluated on the test data. For SARIMAX the best performing model is the one that minimizes the AIC while maintaining a low RMSE, ensuring both a good fit and accurate predictions. The final model is validated by visualizing the actual vs. predicted sales, demonstrating the model's ability to capture the trend and seasonality in sales data.

Model Accuracy Calculation

To further assess model performance, forecast accuracy was calculated using the Mean Absolute Error (MAE) and Root Mean Square Error (RMSE). These metrics measure the average absolute and squared differences between forecasted and actual sales, respectively, with lower values indicating better accuracy. Both MAE and RMSE were calculated for the 90-10 and 95-5 data splits for each drink.

Both metrics provide an easily interpretable measure of performance: MAE gives the average error in actual units, while RMSE, which penalizes larger errors more heavily, provides insight into the model's accuracy with a focus on reducing substantial deviations. These metrics allow for effective comparison of different models and training strategies.

Recursive Forecasting

In time series forecasting, one of the critical components is the ability to predict future values based on past observations. The recursive approach allows for sequential forecasting, where each forecasted value is used as an input to generate the next value in the sequence. The recursive forecast was implemented in both models. After fitting the model to a training dataset, the recursive process begins by making a single forecast for the next time step (e.g., the next month). This forecasted value is then appended to the existing training data, and the model is re-fitted with the new augmented dataset. This process is repeated for 12 months.

BIAS and TISP

BIAS and TISP were also calculated on a monthly basis for the forecasted values, using the actual sales for the corresponding period. These metrics were calculated for both split to evaluate their effectiveness, both of these metrics are metrics used on the daily basis of the company that gave the dataset making a useful method of real word comparison results. BIAS was calculated as the ratio of the forecast error (the difference between forecasted and actual values) to the actual sales. TISP was calculated to evaluate the accuracy of the forecast by measuring how close the forecasted values were to the actual sales. It provides a percentage-based metric that is easy to interpret: a value closer to 1 means the forecast was highly accurate.

$$BIAS = \frac{Forecast - Actual}{Actual} \tag{11}$$

(12)

$$TISP = 1 - \left|\frac{Forecast - Actual}{Actual}\right| 100$$

Bias measures the tendency of the forecast to overestimate or underestimate actual sales (11). A negative Bias indicates overestimation, while a positive Bias indicates underestimation. Meanwhile, TISP (12) ranges from 0 to 100%, with higher percentages representing better forecast accuracy.

Chapter 4

Analysis and Results

4.1. Stationary

4.1.2. Stationary Analysis

From the results of the ADF test, none of the time series of the top 5 SKUs were stationary in their original form (Figure 12 of the appendix). This is confirmed by the p-values, all exceeding 0.05, indicating that the null hypothesis of non-stationarity cannot be rejected, suggesting trends or seasonality in the data. To address the issue of non-stationarity, the series were differenced. The results of the ADF test after applying first-order differencing are summarized in Figure 13 in the appendix.

Figure 4 in the Appendix illustrates the results after differencing of all five time-series (Asti Martini 75CL, Drink Martini Bianco 6CL, Drink Martini Rosso 100CL, Drink Martini Rosso 6CL, and Drink Martini Bianco 100CL) that became stationary. The ADF statistics are negative, and the p-values are all below 0.05, indicating that the null hypothesis of non-stationarity can be rejected for the top 5 SKU. This transformation ensures that the series can be used in time series models and for the Ganger causality test.

In addition to top 5 SKU, the stationarity of external factors was also tested, and these factors were found non-stationary as well, as shown in Figure 10 of the appendix. After applying first-order differencing to the exogenous variables, the series became stationary as it's possible to visualize the results after differencing in Figure 11 of the appendix.

The ADF test results confirm that all the endogenous variables were originally non-stationary but became stationary after applying first-order differencing. Similarly, the exogenous variables such as unemployment, GDP, and overnight stays were also transformed into stationary series through differencing.

4.2. Granger causality test test anaylsis

The heatmaps in the appendix (Figure 14 to 23) show the results of Granger causality tests conducted between Lag 1 and Lag 12. These visual representations aim to determine whether historical values of the external variables can statistically predict the future values of the top SKU, providing key insights into the potential causal relationships within the datasets.

The Granger causality results for Asti Martini 75CL show some degrees of significance across different lags for the external variables. The unemployment rate does not exhibit a consistent Granger-causal relationship with sales for Asti Martini 75CL, with p-values remaining above 0.05 for most lags in both splits. The lowest p-values observed at Lag 3 (0.63) and Lag 12 (0.64) consistently show non-significant p-values, indicating that the GDP is not a Granger cause for this SKU sales in either the 90-10 or 95-5 split. The variable representing the hotel stays at Lag 3, 4 and 5 present lower p-values (0.48, 0.49, and 0.60, respectively), indicating some potential Granger causality, although none of these p-values are below the 0.05 threshold.

For the drink Martini Bianco 6CL, Figures 4.5 and 4.6 show more significant p-values, particularly concerning hotel stays. The unemployment rate shows moderate p-values across lags, with the lowest p-value at Lag 3 (0.63) in the 90-10 split and Lag 4 (0.55) in the 95-5 split. These are not significant, indicating no strong relationship between unemployment and Drink Martini Bianco 6CL sales. Similar to Asti Martini 75CL, the GDP variable does not show a significant Granger causal relationship. All p-values are above 0.05 across both splits. The Granger causality for hotel stays presents a strong causality, at Lag 3 (0.09) and Lag 4 (0.078) in the 95-5 split. These p-values are close to the significance threshold.

The results for Martini Rosso 100CL Show no significant Granger causality for unemployment, with most p-values remaining high. The GDP variable shows potential Granger causality at Lag 5 (0.07) in the 90-10 split, but no strong significant patterns are observed. Hotel stays have the most significant predictive power, p-values drop below 0.05 at several lags, such as Lag 2 (0.0036) and Lag 5 (1.8e-5) in both splits, further reinforcing the critical role of tourism-related activity in predicting sales for this product line.

Drink Martini Rosso 6CL with the unemployment does not exhibit significant causality, as p-values remain above the 0.05 threshold. GDP shows some potential Granger causality at Lag 5 (0.07) in the 90-10 split, but overall, this relationship is not statistically significant. Hotel stays demonstrate strong Granger causality with p-values significantly below 0.05 in Lag 2 (9.4e-5) and Lag 5 (5.2e-5), confirming a predictive relationship between hotel stays and this SKU. The p-values remain significant at several other Lag, highlighting the importance of tourism-related variables for this product line.

For Drink Martini Bianco 100CL, there is strong evidence that the variable representing hotel stays is Granger-causal for sales (Figures 22 and 23 from appendix). P-values remain generally non-significant across all lags for the unemployment variable. Similar to the previous product lines, the GDP variable does not show a significant Granger causality relationship. For hotel stays, p-values fall significantly below 0.05 in several lags, especially Lag 2 (1e-5) and Lag 5 (2.3e-5) in the 95-5 split. These results strongly indicate that hotel stays Granger-cause Drink Martini Bianco 100CL sales, particularly at shorter lags.

4.3. Modelling phase

4.3.1. SARIMAX

The SARIMAX model was implemented for each SKU dataset with the objective to capture the patterns in sales data with the best external exogenous factors that were calculated in the previous chapter. Figures 24 to 28 provided in the appendix illustrate the comparisons between actual and predicted sales across the two splits, providing a visual representation of how closely the SARIMAX models could capture the trends and seasonality in sales for the different top 5 SKU. For each drink, forecasts were generated for the last 12 months of actual sales and compared against the actual values.

Forecasts for the next 12 months were also produced as recursive forecasts. The model parameters and seasonal components that were obtain in the forecasting model can be seen on the Figure 34 on the appendix.

Table 4.1 - Comparison of MAE and RMSE for SARIMAX Forecasting 90-10 and 95-5

Drink	MAE (90-10)	RMSE (90-10)	MAE (95-5)	RMSE (95-5)
Asti Martini 75CL	43.8	54.55	25.30	28.42
Martini Bianco 6CL	57.17	67.36	27.14	40.5
Martini Rosso 100CL	1195.18	1540.05	1435.61	1853.23
Martini Rosso 6CL	3908.44	5231.01	3496.8	43839.3
Martini BIanco 100CL	370.65	481.23	301.54	367.19

According to Table 4.1 for the Asti Martini 75CL the 90-10 split model produced an MAE of 43.8 and an RMSE of 54.55, when the 95-5 split model achieved slightly better accuracy with a lower MAE of 25.30 and RMSE of 28.42. This indicates that the 95-5 split offers slightly better performance in predicting sales for Asti Martini 75CL. The visual comparison between actual and predicted sales on the Figure 24 of the appendix shows significant increase in accuracy for the 95-5 split indicates that this model benefits from more training data and smaller test data.

For Drink Martini Bianco 6CL, the 90-10 split resulted in an MAE of 57.17 and an RMSE of 67.36, while the 95-5 split showed a significant improvement with an MAE of 27.1 and RMSE of 40.5. This shows a similar trend as Asti Martini 75CL, where more training data helps improve the model's predictive power.

On the Drink Martini Rosso 100CL was experienced significantly errors. The MAE for the 90-10 split was 1195.18 with an RMSE of 1540.05, and for the 95-5 split, the MAE increased to 1435.61 with an RMSE of 1853.23. Showing a better result of accuracy on the spli 90-10. The high RMSE values indicate that the model struggles to capture the volatility of Drink Martini Rosso 100CL's sales.

Drink Martini Rosso 6CL, presents an MAE for the 90-10 split at 3908.44 and an RMSE at 5231.01, while the 95-5 split model had an MAE of 3496.8 and RMSE of 43839.3.

Drink Martini Bianco 100CL had a MAE of 370.65 and RMSE of 481.23 for the 90-10 split, while the 95-5 split resulted in an MAE of 301.54 and RMSE of 367.19.

4.3.2. Prophet

The Prophet model was implemented for each SKU dataset with the objective of capturing the patterns in sales data while utilizing the best external exogenous factors, similar to the SARIMAX model. The comparison between actual and predicted sales was made across two splits (90-10 and 95-5) to evaluate the model's ability to forecast sales trends and seasonality for the top 5 SKUs.

Table 4.2 Prophet MAE and RMSE for each drink in both 90-10 and 95-5 splits based

Drink	**MAE (90-10)**	**RMSE (90-10)**	**MAE (95-5)**	**RMSE (95-5)**
Asti Martini 75CL	77.22	82.47	63.05	85.45
Martini Bianco 6CL	57.56	67.98	57.55	67.05
Martini Rosso 100CL	2616.99	3054.21	2641.44	2994.58
Martini Rosso 6CL	6029.59	7100.92	6239.54	7091.43
Martini Blanco 100CL	675.01	722.05	750.84	788.54

For Asti Martini 75CL giving the Table 4.2, the 90-10 split model resulted in an MAE of 77.22 and an RMSE of 92.47, whereas the 95-5 split model produced slightly improved accuracy, with an MAE of 63.05 and an RMSE of 85.45. The slight improvement in performance for the 95-5 split suggests that additional training data enhances the model's ability to predict future sales. The visual comparison between actual and predicted sales shows better alignment in the 95-5 split in the appendix Figure 29 to 30, particularly toward the end of the testing period, where the model was better able to capture the sales patterns.

For Drink Martini Bianco 6CL, the Prophet model in the 90-10 split yielded an MAE of 57.56 and an RMSE of 67.98, while the 95-5 split produced an MAE of 57.55 and an RMSE of 67.05. The model was able to capture the general sales trends, but the relatively close performance between the two splits suggests that the Prophet model for Drink Martini Bianco 6CL did not benefit significantly from the additional training data in the 95-5 split.

Drink Martini Rosso 100CL experienced significantly higher errors, with an MAE of 2616.99 and an RMSE of 3054.21 for the 90-10 split. The 95-5 split showed similar results, with an MAE of 2641.44 and an RMSE of 2994.58. Although the RMSE values for Drink Martini Rosso 100CL were large, the accuracy remained relatively high, indicating that while the model struggled with exact predictions, it was still able to capture the overall trend and seasonality in sales data.

The Prophet model showed weaker performance for Drink Martini Rosso 6CL, with the 90-10 split yielding an MAE of 6029.59 and an RMSE of 7100.92, and the 95-5 split resulting in an MAE of 6239.54 and an RMSE of 7091.43.

For Drink Martini Bianco 100CL, the 90-10 split model produced an MAE of 675.01 and an RMSE of 722.05, while the 95-5 split model resulted in an MAE of 750.84 and an RMSE of 788.54. The model was able to capture the sales trends fairly well, with the 90-10 split offering slightly better performance in terms of accuracy compared to the 95-5 split.

Recursive Forecasting

Two distinct forecasting models were employed: Prophet and the SARIMA model, each one was used depending on the best accuracy from the best split. In Table 4.5, it’s possible to see the forecasted sales for the five top SKU (Asti Martini 75CL, Martini Bianco 6CL, Martini Rosso 100CL, Martini Rosso 6CL and Martini Bianco 100CL) based on a 95-5 split using SARIMAX models for the Asti Martini 75CL, Martini Bianco 6CL, Martini Rosso 6CL, and Martini Bianco 100CL, and 90-10 split Drink Martini Rosso 100CL. The results show monthly predictions from April 2024 to March 2025.

Table 4.3 - Recursive Forecast for the Next 12 Months for the TOP 5 SKU

Date	Asti Martini 75CL SARIMAX (95-5 split)	Martini Bianco 6CL SARIMAX (95-5 split)	Martini Rosso 100CL SARIMAX (90-10 split)	Martini Rosso 6CL SARIMAX (95-15 split)	Martini Bianco 100CL SARIMAX (95-5 split)
2024-04-01	94.98	133.42	4409.56	17154.67	802.66
2024-05-01	108.82	179.64	6156.75	12409.31	827.50
2024-06-01	118.50	123.33	6000.64	15100.85	1670.32
2024-07-01	140.50	201.56	8862.22	28105.19	2655.24
2024-08-01	27.00	72.77	9855.46	4660.88	-176.21
2024-09-01	41.50	207.63	7745.14	9853.00	165.75
2024-10-01	125.00	90.00	7793.24	7224.27	337.27
2024-11-01	153.50	232.82	8285.30	16668.67	1029.53
2024-12-01	230.00	249.63	11422.92	19494.36	2263.74
2025-01-01	235.50	159.53	4262.88	17951.73	2012.94
2025-02-01	112.50	163.34	4526.61	12350.24	1171.00
2025-03-01	206.50	286.03	5314.62	26173.07	1909.03

Asti Martini 75CL shows an increasing trend in sales, starting at 94.98 in April 2024 and peaking at 235.50 in January 2025. In the month of August, it is possible to see a decrease of sales to the value 27.00 in August 2024. By March 2025, sales are predicted to rise again to 206.50. Drink Martini Bianco 6CL begins at 133.42 in April 2024, rising to a high of 249.97 in December 2024 before dropping to

159.63 in January 2025 and 163.34 in February 2025. The forecast predicts a further increase to 286.03 in March 2025. Drink Martini Rosso 100CL starts with 4409.56 of sales in April 2024 and reached a peak of 11422.92 in December 2024. Sales fluctuate considerably, with peaks in August (9855.46) and October (8285.30), and a drop to 4262.88 in January 2025. By March 2025, the forecast stabilizes at 5314.62. Drink Martini Rosso 6CL starts at 17154.67 in April 2024, peaks at 28105.19 in July 2024, and then declines significantly to 4660.88 by August 2024, reaching 19494.36 in December 2024 and 26173.07 by March 2025. Drink Martini Bianco 100CL begins at 802.66 in April 2024, increasing to 2655.24 of sales.

Asti Martini 75CL and Drink Martini Bianco 6CL show a relatively steady upward trend in sales, with a few periods of decline, but both are expected to end the forecast period in growth. Drink Martini Rosso 100CL displays a highly volatile forecast, with large peaks and drops, but a generally increasing trend towards the end of the period. Drink Martini Rosso 6CL experiences significant mid-year volatility, with a large dip followed by recovery, suggesting potential external factors influencing mid-2024 sales. Drink Martini Bianco 100CL shows the most extreme volatility, including a negative forecast for August 2024, before recovering in the months thereafter.

4.4. Bias and TISP

Was used the model that fits the lowest RMSE and MAE to test the Bias and TISP against the real sales values, the analysis of sales forecast was performed across seven months (from September 2023 to March 2024). The alignment between the forecasted data with the real-world sales was analyzed for the top 5 SKU focusing on both individual products and the overall performance over time. The best and worst months were identified for forecasting accuracy according to the test dataset, based on the Bias and TISP metrics Table 4.4, as well as the overall year-to-date (YTD) performance in Table 4.5.

Table 4.4 - BIAS and TISP values for the TOP 5 SKU

Drinks	set/23		out/23		nov/23		dez/23		jan/24		fev/24		mar/24	
	BIAS	TISP	BIAS	TISP	BIAS	TISP	BIAS	TISP	BIAS	TISP	BIAS	TISP	BIAS	TISP
Asti Martini 75 CL	-67%	33%	-48%	52%	-41%	59%	-12%	88%	-70%	30%	27%	73%	-65%	35%
Martini Bianco 6CL	-77%	23%	6%	94%	-8%	92%	-5%	95%	-9%	91%	-21%	79%	40%	60%
Martini Rosso 100CL	-26%	74%	-20%	80%	-46%	54%	57%	43%	-58%	42%	-48%	52%	-63%	37%
Martini Rosso 6CL	-10%	90%	-10%	90%	-62%	38%	12%	88%	-62%	38%	-47%	53%	-29%	71%
Martini Bianco 100CL	19%	81%	17%	83%	-60%	40%	26%	74%	-274%	374%	-48%	53%	-10%	90%
Total	-14%	85%	-12%	86%	-57%	43%	24%	76%	-54%	32%	-47%	53%	-43%	57%

Martini Rosso 100CL

The best month recorded for drink Martini Rosso 100CL was October 2023, with a Bias of -20% and a TISP of 80%, these results indicate a moderate overestimation, but with high accuracy. The gap between forecasted and actual sales was only 1231.14 units. The worst month was March 2024, with a Bias of -63% and a TISP of 37%. The forecast significantly overestimated demand by 3257.89 units, which resulted in low accuracy. On the YTD Performance: Over the year, drink Martini Rosso 100CL had a YTD Bias of -17%, reflecting a tendency toward overestimation, and a YTD TISP of 55%.

Asti Martini 75CL

For Asti Martini 75CL the best month was December 2023, with a Bias of -12% and a TISP of 88%, with a difference of 17.50 sales, showing that the forecasting model performed well for this product. The worst was month was January 2024 with a Bias of -70% and a TISP of 30%. Across the year, the YTD Bias was -41% and a YTD TISP of 55%, with a total of 293.80 units between forecasted and actual sales.

Drink Martini Rosso 6CL

The forecasting model performed consistently well for drink Martini Rosso 6CL in both September and October 2023, with a Bias of -10% and a TISP of 90% in each month. The forecasts in these months were highly accurate, and November saw the worst performance, with a Bias of -62% and a TISP of 38%. The YTD Bias for this drink was -19%, and presents a YTD TISP of 73%.

Drink Martini Bianco 100CL

March 2024 was the best-performing month for Martini Bianco 100CL, with a Bias of -10% and a TISP of 90%. The forecast was highly accurate, with a small Gap of only 66.67 units between forecasted and actual sales, the month of January 2024 showed a negative value of Bias -274% and a TISP of 374%, reflecting a major underestimation of demand. Over the year, Drink Martini Bianco 100CL had a YTD Bias of 4%, reflecting a slight underestimation of demand overall, and a YTD TISP of 60%.

Drink Martini Bianco 6CL

The month of October 2023 was the most accurate for drink Martini Bianco 6CL with a Bias of 6% and a TISP of 94%. The worst month was September 2023 with a Bias of -77% and a TISP of 23%. the YTD Bias was -13%, indicating a moderate overestimation of demand, and the YTD TISP was 79%, reflecting good overall accuracy.

Table 4.5 YTD BIAS and TISP values for the top 5 SKU

Drinks	**YTD**	
	BIAS	**TISP**
Asti Martini 75CL	-41%	55%
Martini Bianco 6CL	-13%	79%
Martini Rosso 100CL	-17%	55%
Martini Rosso 6CL	-19%	73%
Martini BIanco 100CL	4%	60%
Total	-18%	67%

YTD

The overall YTD Bias for the forecasting of the top 5 SKU was -18%, indicating a tendency to overestimate sales across products. The YTD TISP was 67%, reflecting moderate forecast accuracy.

Chapter 5

Discussion

This chapter aims to discuss the key findings of the results presented in the previous chapter, focusing on the application of forecasting models such as SARIMAX and Prophet in predicting sales within the spirits industry for the sector on-trade, adding the analysis of the Bias and TISP metrics, which provide deeper insights into the model´s accuracy and overestimation tendencies. Additionally, the influence of the external factors was studied to provide a more complete understanding of the use of demand drivers on the on-trade channel. This chapter also discusses the implications of these findings for business goals and offers suggestions for future improvements, answering the three main research questions based on the insights gained from the results chapter.

SARIMAX vs. Prophet

The results and the comparison between the forecasting models SARIMAX and Prophet (Figure 24 to Figure 33 from the appendix) revealed that SARIMAX performed better across the top 5 SKU, achieving higher accuracy levels, especially when using a 95-5 data split. This result aligns with the established advantages of SARIMAX, which is known for effectively capturing complex seasonality, autoregressive components, and moving average processes within time-series data.

Table 5.1 Results for the test dataset SARIMAX and PROPHET model across the two splits

	SARIMAX				PROPHET			
Drink	**MAE (90-10)**	**RMSE (90-10)**	**MAE (95-5)**	**RMSE (95-5)**	**MAE (90-10)**	**RMSE (90-10)**	**MAE (95-5)**	**RMSE (95-5)**
Asti Martini 75CL	43.8	54.55	25.30	28.42	77.22	82.47	63.05	85.45
Martini Bianco 6CL	57.17	67.36	27.14	40.5	57.56	67.98	57.55	67.05
Martini Rosso 100CL	1195.18	1540.05	1435.61	1853.23	2616.99	3054.21	2641.44	2994.58
Martini Rosso 6CL	3908.44	5231.01	3496.8	43839.3	6029.59	7100.92	6239.54	7091.43
Martini Blanco 100CL	370.65	481.23	301.54	367.19	675.01	722.05	750.84	788.54

Data Split Impact: 95-5 vs. 90-10

The results indicate that the 95-5 split provided more accurate forecasts than the 90-10 split, emphasizing having a larger training dataset to enhance model learning. A more extensive training dataset allows the model to better capture historical trends, seasonality, and other patterns, resulting in more accurate predictions when tested on the remaining 5% of the data. This insight is particularly useful for businesses that may need to balance between training their models on a large proportion of historical data while still ensuring they have enough recent data left for testing and validation. The improved performance with the 95-5 split suggests that for similar forecasting tasks, companies should prioritize training models on as much historical data as possible, while using a small portion of recent data to test accuracy and fine-tune the model. The results demonstrate that splitting the dataset into 95-5 generally improves the accuracy of the sales predictions for all the drinks, in both models.

5.1. Model Selection for the different types of drinks

This section shows the evaluation of predictive models for the top 5 SKU, comparing the performance of SARIMAX and Prophet models. The Table 5.1 showed the comparison of MAE and RMSE for SARIMAX forecasting using 90-10 and 95-5 data splits and the same comparison for the Prophet model.

The following analysis of each SKU demonstrates how well the models could capture sales data fluctuations. This comprehensive assessment provides insights into the strengths and limitations of SARIMAX and Prophet across different forecasting scenarios.

Asti Martini 75CL

For Asti Martini 75CL, the mean monthly sales for this product were approximately 158.25 sales, this value provides a baseline to contextualize the model errors as a percentage of typical sales. In the 90-10 split, Prophet produced an MAE of 77.22, this value signifies that this forecast are 77.22 sales off from the actual sales figures. An RMSE of 82.47, reflects the model's typical forecast error, with slightly more weight given to larger errors. Comparatively, the SARIMAX model achieved a much lower MAE of 43.97 sales off and RMSE of 54.55, this happens because, in RMSE, each error is squared before averaging, so any big mistakes in predictions have a larger impact on the final RMSE.

A similar trend was observed in the 95-5 split, where Prophet recorded an MAE of 63.05 and RMSE of 85.45. In contrast, SARIMAX achieved an MAE of 25.30 and RMSE of 28.42, this corresponds to 18% of mean sales, demonstrating that the model's typical forecast error is relatively low and consistent.

These results indicate that SARIMAX captured the sales patterns of Asti Martini 75CL more effectively than Prophet, particularly in the 95-5 split where the model had more training data and a smaller test set. The lower RMSE and MAE values for SARIMAX suggest that it was able to better handle fluctuations in sales and predict more accurate values for future periods.

Martini Bianco 6CL

The results for Drink Martini Bianco 6CL further demonstrate the superiority of SARIMAX over Prophet, particularly in the 95-5 split. Having an average of 146.14 sales, in the 90-10 split, Prophet generated an MAE of 57.56 and an RMSE of 67.98. An MAE of 57.56 means that, on average, Prophet's forecasts were 57.56 sales difference from actual sales, while an RMSE of 67.98 indicates that occasional larger errors in Prophet's predictions slightly increased the average error.

Meanwhile, SARIMAX outperformed with an MAE of 43.8 and RMSE of 54.55. However, the performance gap widened in the 95-5 split. Prophet's performance remained consistent, producing an MAE of 57.55, RMSE of 67.05. On the other hand, SARIMAX demonstrated a significant improvement, recording an MAE of 27.14 and an RMSE of 40.5.

The performance of SARIMAX in the 95-5 split highlights the model's ability to improve its predictive power when provided with more training data, similar to the trend observed with Asti Martini 75CL. The drastic reduction in RMSE and MAE for SARIMAX in this split shows its enhanced capacity to capture both long-term trends and short-term variations on the drink Martini Bianco 6CL's sales. Prophet's relatively consistent performance across the two splits suggests that while it can capture the general trend of sales, it does not fully benefit from the additional training data. This could be due to its limitation in handling complex fluctuations, in which SARIMAX is better equipped to manage through its more detailed model structure.

Martini Rosso 100CL

The performance of Prophet and SARIMAX for Drink Martini Rosso 100CL presented mixed results. In the 90-10 split, Prophet recorded an MAE of 2616.99 and an RMSE of 3054.21, associating to around 44% and 51% of the average monthly sales (average per month was 5,935.16 sales), these high error rates suggest that Prophet's forecasts were frequently quite far from actual sales values, showing limited precision. SARIMAX, on the other hand, achieved a lower MAE of 1195.18 (20% of mean sales) and RMSE of 1540.05 (26% of mean sales), indicating significantly closer predictions to actual sales values.

In the 95-5 split, Prophet's MAE increased to 2641.44 and its RMSE remained relatively high at 2994.58. In this case SARIMAX RMSE and MAE were increased as well, recorded an MAE of 1435.61 and RMSE of 1853.23.

Overall, SARIMAX's performance, especially in the 90-10 split, emphasizes its strength in achieving better precision.

Martini Rosso 6CL

For Drink Martini Rosso 6CL, SARIMAX outperformed Prophet significantly, as Prophet struggled with highly volatile sales patterns for this SKU. In the 90-10 split, Prophet generated an MAE of 6029.59 and an RMSE of 7100.92, indicating substantial deviations in its forecasts. SARIMAX, on the other hand, produced a much lower MAE of 3908.44 and RMSE of 5231.01. When compared to the average

monthly sales of 13,492.86 units, these error values show that SARIMAX was, on average, about 29% off from actual sales (MAE), while Prophet deviated by 45% of mean sales.
Similarly, in the 95-5 split, Prophet recorded an MAE of 6239.54 and an RMSE of 7091.43, while SARIMAX delivered a better value MAE of 3496.8 of difference from the actual sales and a the RMSE of 4389.3.

The vast performance gap between Prophet and SARIMAX for Drink Martini Rosso 6CL can be attributed to the volatility in sales for this SKU. SARIMAX's ability to account for autoregressive processes and moving averages allowed it to better capture these fluctuations, whereas Prophet's reliance on smooth trends and seasonal patterns proved insufficient.

Martini Bianco 100CL

For Drink Martini Bianco 100CL, SARIMAX again demonstrated stronger performance than Prophet. In the 90-10 split, Prophet recorded an MAE of 675.01 and an RMSE of 722.05, which represent about 47% and 51% of the average monthly sales, respectively. SARIMAX outperformed these values with an MAE of 370.65, RMSE of 481.23. The 95-5 split revealed a similar pattern, with Prophet achieving an MAE of 750.84, RMSE of 788.54, while SARIMAX showed a value of MAE of 301.54 (21% of mean sales) and an RMSE of 367.19 (26% of mean sales).

These results suggest that SARIMAX was more effective in capturing the sales trends for the drink Martini Bianco 100CL, particularly when more training data was available in the 95-5 split. Prophet's performance remained relatively consistent, but SARIMAX's ability to adjust to short-term sales changes contributed to its lower error metrics and higher accuracy. The improved performance of SARIMAX in the 95-5 split, as seen with other SKUs, emphasizes the benefit of providing more data for training, which enhances the model's ability to capture complex patterns and seasonality.

Table 5.2 Best Performing Forecasting Models for Different Drink Products use RMSE accuracy

Drinks	**Best Model**	**Best Split**
Asti Martini 75CL	SARIMAX	95-5 Split
Martini Bianco 6CL	SARIMAX	95-5 Split
Martini Rosso 100CL	SARIMAX	90-10 Split
Martini Rosso 6CL	SARIMAX	95-5 Split
Martini BIanco 100CL	SARIMAX	95-5 Split

In selecting which prediction models can be used for the different types of drinks, the SARIMAX model was the best performer for five out of five beverages as show in Table 5.2. The relatively low values of MAE and RMSE of these models demonstrates their capacity to capture seasonal trends, especially for products with significant seasonality, such as beverages that experience high demand during holidays or specific periods.

The SARIMAX model with the 95-5 split was proved effective for drinks with regular, seasonal consumption patterns. Beverages like Asti Martini 75CL and Martini Bianco 100CL exhibit predictable demand trends, making SARIMAX an ideal choice. Its high accuracy and ability to incorporate exogenous variables make it robust for beverages that are heavily affected by external factors such as promotions, pricing, and holidays.

The results suggest that SARIMAX is generally a robust choice for forecasting sales in this sector, particularly when larger training datasets are available. SARIMAX's ability to incorporate both time series data and external regressors makes it an ideal model for capturing seasonal trends, consumer behavior, and exogenous factors such as tourism.

However, for products with more complex or non-linear patterns, the split 90-10 provides better accuracy, having the ability to handle irregular time-series data with robust seasonality adjustments, when consumer behavior is less predictable, for beverages like Martini Rosso 100CL, which exhibit more complex demand patterns (such as larger spikes and drops) these findings underline the importance of a well-balanced test set in achieving reliable forecasting accuracy, particularly for products with highly variable sales patterns.

5.2. External factors and their Impact on Forecast Accuracy

A substantial finding of this research, and one of the main objectives, was the influence of external factors on sales performance. In this regard, it was concluded that external factors, particularly tourism related variables, are an important feature for the forecast of spirits industry.

Using the Granger causality test, it was found that variables such as hotel stays have a strong predictive relationship with sales. This finding is highly relevant for forecasting models, as it suggests that businesses should include tourism data as part of their exogenous variables when predicting sales demand.

Drink Martini Rosso 6CL exhibited high forecast accuracy when short-term Lag of 2 to 5 months were incorporated, highlighting the Lagged effect of tourism on sales. This shows that the impact of external tourism factors does not immediately reflect in sales, but rather follows a short delay, likely due to the nature of consumer purchasing patterns in the on-trade market. On the other side, broader economic indicators such as GDP and unemployment rates were not found to have a significant Granger-causal effect on beverage sales. This finding underscores the sector's sensitivity to specific external factors (like tourism) rather than macroeconomic conditions. This implies that the on-trade beverage sector is more sensitive to tourism and sector-specific factors than to broader macroeconomic conditions. This observation is important for businesses in this sector, as it suggests that tourism data should be a primary input in sales forecasting models.

Tourism as a Key Exogenous Variable

This study highlights the importance of incorporating tourism-related data in forecasting models for the on-trade channel in the spirits industry. The results identified that tourism, particularly hotel stays, is a critical driver of demand in the on-trade. Beverage companies should consider integrating real-time or near-real-time tourism data into their forecasting systems to anticipate demand surges related to tourism peaks. Companies can use predictions about upcoming tourist seasons to adjust their inventory levels and marketing campaigns in advance to achieve a better balance between the sell-in and sell-out distribution methods. While economic factors, such as GDP and unemployment rates, appeared less relevant to the specific sales patterns of the beverages.

5.3. Bias and TISP Performance Across Top 5 SKUs

Incorporating the metrics Bias TISP and their analysis across the top 5 SKUs from September 2023 to March 2024 reveals several important insights into the strengths and limitations of the current forecasting models. By assessing both the Bias and TISP values, it was possible to understand how well the forecasted sales align with actual sales and which improvements may be necessary. While some months showed strong alignment between forecasted and actual sales (March 2024 for Martini Bianco 100CL with a TISP of 90%), other months suffered from significant gaps (November 2023 for the same product, with a TISP of 40%), the YTD TISP for the top SKUs, presents a value of 67%, falling below the target of 75%, indicating moderate accuracy, it also has an overestimation bias, of -18%, this negative bias indicates that the model consistently overestimated sales across most SKUs, predicting higher demand than what was realized in actual sales data.

These results may come from the model's inability to adapt quickly to shifts in demand caused by external factors or unexpected changes in consumer behavior that are not being considered in this research.

The SKU Martini Rosso 100CL demonstrated a YTD Bias of -17% and a TISP of 55%, reflecting an overestimation of sales in the overall YTD results. This overestimation could be attributed to external factors not reflected in the historical data used for the forecast. The model's dependence on past sales data without incorporating real-time market changes limited the ability to adjust for these fluctuations. In the case of Asti Martini 75CL, this SKU was the largest overestimation, with a Bias of -41%, this value can also be explained by the low sales values, making it more challenging for the model to capture demand patterns, as there is less data available to establish reliable trends. The fewer sales transactions there are, the more difficult it is for the model to accurately predict future demand based on historical data, leading to greater forecast volatility and more significant forecasting errors.

In contrast, SKUs with more sales, like Martini Rosso 6CL, obtained a TISP of 73% with a Bias of -19%, both of these values indicate that the model was able to better align with actual sales data for this SKU, likely due to more stable and predictable demand patterns. However, the continuous overestimation, shows that further improvements are needed.

Martini Bianco 100CL showed a Bias of 4%, indicating slight underestimation, but the TISP of 60% reflects moderate forecast accuracy, suggesting that the model still struggled to capture short-term demand fluctuations. Martini Bianco 6CL, on the other hand, performed the best, with a TISP of 79% and a Bias of -13%, indicating good alignment between forecasted and actual sales.

Incorporating more dynamic variables, for example, marketing campaigns, consumer trends, and external market conditions, could help to improve these values. Without accounting for such variables, the models rely heavily on historical sales patterns, which may not always reflect current market realities, leading to inaccuracies. Additionally, adjusting the forecast for variations in demand throughout specific periods (e.g., holiday seasons or off-peak months) could improve the accuracy.

Furthermore, segmenting products based on their demand characteristics (e.g., high-volume vs. low-volume SKUs) with more sensitive data, day-to-day sales and a continuous feedback loop to monitor forecast accuracy in real-time, allowing for rapid adjustments to the model when inaccuracies are detected, may help to prevent large discrepancies from persisting throughout the year.

Upon analyzing the results for each SKU, it becomes clear that the model's performance varied significantly based on the product and the time period in question.

5.4. How can the discrepancy Between Sell-In and Sell-Out mitigate

Using Predictive Models to Align Supply with Demand

One of the most effective ways to mitigate the discrepancy between sell-in and sell-out is by utilizing forecasts methods, such as models like SARIMAX and Prophet.

The predictive models, SARIMAX and Prophet, provide accurate demand forecasts for different beverages, allowing manufacturers and retailers to adjust their orders (sell-in) based on expected consumer purchases (sell-out). By doing this, overstocking or understocking can be avoided, ensuring that the sell-in more closely matches the actual sell-out.

For example, Asti Martini 75CL shows a forecasted peak in December and January of 2024 (230 and 235 units) and a significant drop in February (112.50 units). Distributors can use this forecast to place larger sell-in orders leading to December, anticipating the holiday demand spike. However, they can reduce orders post-December and January to avoid overstocking, matching the forecasted drop in demand in February.

For the Martini Bianco 6CL a peak in November and December 2024 (232,82 and 249.97 units) is predicted, with a sharp drop in January (159.63 units). Retailers can optimize their sell-in for the peaks and quickly reduce it afterward to match the forecasted sell-out, thus mitigating overstocking risks in the quieter months.

In the case of the SKU Martini Rosso 100CL, it demonstrates more extreme fluctuations, with sales peaking in December (11,422.92 units) and dropping sharply to 4,526.61 units in January. Using this information, businesses can adjust their orders to ensure they are not left with excessive stock after the holiday period, preventing an overstock situation.

These models can be integrated into inventory management approaches, where stock levels are replenished dynamically based on real-time data. For example, suppose a model predicts a sudden drop in demand for Martini Bianco 6CL in October (80.49 units). In that case, businesses can immediately reduce their inventory, ensuring that sell-in orders align with this reduced sell-out forecast. If the model predicts a sudden increase in sales for a specific period (Asti Martini 75CL in July with 140.50 units), businesses can proactively increase sell-in orders to meet this demand and avoid stockouts.

If a forecast indicates that demand is going to drop in the future (as seen with several products in January and February), businesses can run targeted promotions to stimulate sales and avoid a sell-in/sell-out discrepancy. If the forecast predicts a drop in sales for Martini Rosso 100CL after December, businesses can run promotions in January to encourage more purchases, moving excess stock that might otherwise remain unsold.

Real-time adjustments in inventory levels based on predictive model outputs will ensure that the discrepancy between sell-in and sell-out is minimized, thus enhancing operational efficiency.

5.5. Key Finding

This research has helped highlight the complexities of developing an accurate forecasting model, especially when dealing with multiple SKUs with different demand patterns. One key finding is the importance of building adaptive models that can account for variability in demand across different products and time periods.

The systematic overestimation represented in the metrics of the real case company shows that another key finding is the incorporation of external factors, holidays and product-specific behavior to achieve a better forecast. This realization has driven an understanding of the limitations of traditional forecasting models and the value of implementing more advanced techniques. Other key finding is the presence of low sales values significantly impacting the forecasting models' results, thus preventing the model's ability to attain a high accuracy and reliable predictions, for example, small absolute changes in demand may lead to large percentage errors in Bias and TISP, these low-sales products are often more volatile and more sensitive to external factors.

Additionally, the project has reinforced the idea that forecasting is an iterative process. No single model will be perfect, and continuous improvement is crucial to improve accuracy over time.

Through this process, it's possible to learn the importance of flexibility in model design and the need for constant validation and recalibration to ensure that forecasts remain relevant in changing market conditions.

Ultimately, this research has provided valuable lessons in forecasting challenges, emphasizing the importance of adaptability, precision, and continuous improvement. By applying these lessons and recommendations, future forecasting models can achieve higher accuracy and better serve operational and strategic decision-making needs.

Chapter 6

Conclusion and Recommendations

This research has provided several contributions to understanding and improving sales forecasting in the spirits beverages sector, particularly for the on-trade channel. By comparing the performance of SARIMAX and Prophet, it's possible to highlight the strengths and limitations of each model in predicting sales for the top five SKUs. Overall, SARIMAX with the 95-5 split outperformed all the models, particularly for products that exhibited strong seasonality and dependence on external factors. However, the split 90-10 demonstrated its strengths in products with more complex demand patterns, such as Martini Rosso 100CL, where it better handled irregular time series and seasonal variations. The study found that different products require personalized forecasting approaches to each one.

The study also demonstrated that data split strategies, between 95-5 and 90-10, revealed that strategies using a larger portion of historical data (95-5 strategy) for training, improved the accuracy of the forecasting models. This highlights the value of having extensive training data to enhance model learning and predictive performance.

Other discovery of this research is the impact of external factors, particularly tourism-related variables, on sales forecasts. The Granger causality test revealed that tourism data, such as hotel stays, has a strong predictive relationship with sales, while economic indicators like GDP and unemployment rates were found to have a limited impact on sales forecasts in the on-trade segment. This discovery emphasizes the need for businesses in the beverage sector to incorporate tourism-related data as a key exogenous variable, in change of macroeconomic trends, in their forecasting models to anticipate demand surges and optimize inventory management.

Using Bias and TISP metrics provided additional insights into the performance of the forecasting models. The overall YTD Bias of -18% reflected a systematic overestimation of demand, which was particularly pronounced in products with low sales volumes, such as in the case of the SKU Asti Martini 75CL, in which the low sales values prevented the model to establish reliable trends, leading to a higher volatility and larger percentage errors in Bias and TISP. On the other hand, SKUs with more stable sales patterns and higher sales, like Martini Rosso 6CL, performed better, indicating that the model was more accurate when predicting demand for products with higher sales.

In addition to analyzing forecasting accuracy, the study also explored the discrepancy between sell-in and sell-out and how predictive models like SARIMAX and Prophet can help businesses align their supply with actual consumer demand, providing an invaluable tool for mitigating the discrepancies between sell-in and sell-out. By using accurate sales forecast models, companies can adjust their inventory levels, reduce wastage from overstocking, avoid missed sales opportunities due to stockouts, and use promotional strategies to minimize the risks of overstocking, improving their data-driven decisions and ultimately reducing the gap between sell-in and sell-out.

6.1. Limitations and Future Research Directions

Despite valuable insights, the forecasting models exhibited some limitations, resulting in the results revealed, an overall Bias of -18% and an TISP of 67%, suggest the need for improvements to better align forecasts with actual sales. These results of the forecast models between SKUs suggests that the approach of using the data sale history and the use tourism related external variables may not be sufficient. Although this research provided valuable insights, there are several areas where future research could improve the findings and the results of the forecasting. For example, personalizing each model to each SKU by considering their unique demand drivers (e.g., customer segmentation, market share, promotional insights and market trends) will likely improve forecast precision. Future research could explore the integration of additional exogenous variables, such as local events, or weather conditions. Including these variables could improve forecast accuracy, especially for products sensitive to such external influences. Another key finding for future research direction is the incorporation of more data, such as daily or weekly sales. This could improve the responsiveness of forecasting models to short-term trends and events.

This experience has provided valuable lessons in adapting forecasting models and it is clear that future researches should incorporate these complexities to achieve better accuracy in future forecasts. This reflection on the limitations of the current models has extended my understanding of forecasting challenges and has also provided me with practical ideas for future improvements.

6.2. Final Considerations

In conclusion, the findings from this study provide a strong foundation for improving sales forecasting in the spirits industry. By adopting advanced forecasting models, integrating external variables like tourism, and tailoring approaches to individual products, businesses can significantly enhance the accuracy of their demand predictions. This will lead to better inventory management, more efficient supply chains, and ultimately, increased profitability in a highly competitive market. The thesis provides a solid framework for decreasing the discrepancies between sell-in and sell-out processes, offering a competitive advantage by aligning sales strategies with forecast models.

While the applied models revealed some limitations, the lessons learned offer valuable guidance for future improvements. By incorporating the recommended adjustments, such as integrating more dynamic external variables, developing SKU-specific models, and implementing real-time adjustment mechanisms, forecast results can be significantly enhanced.

The main lesson learned in this research is the importance of continuous model refinement and adaptability, forecasting is not a one-time process, but an ongoing one. Iterative tasks that requires constant validations, recalibrations and continuously evolution of techniques and knowledge are essential for businesses' success as the market of the spirits beverages change.

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Appendix

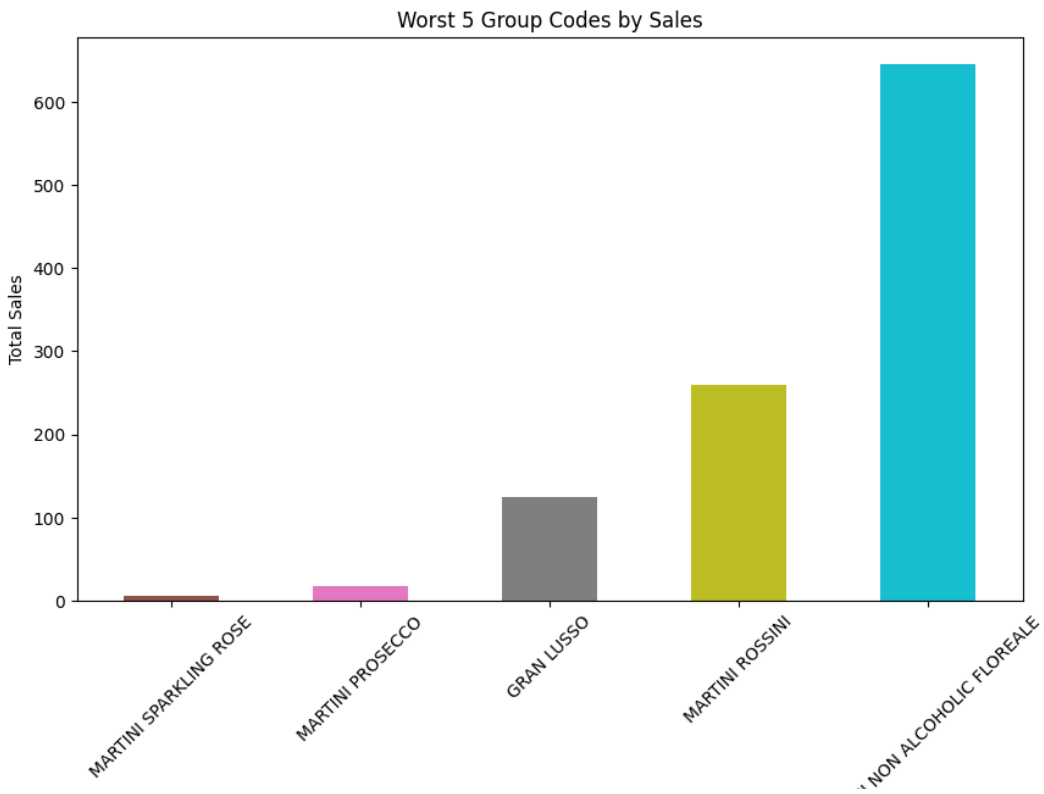


Figure 1 - Worst 5 Group Code

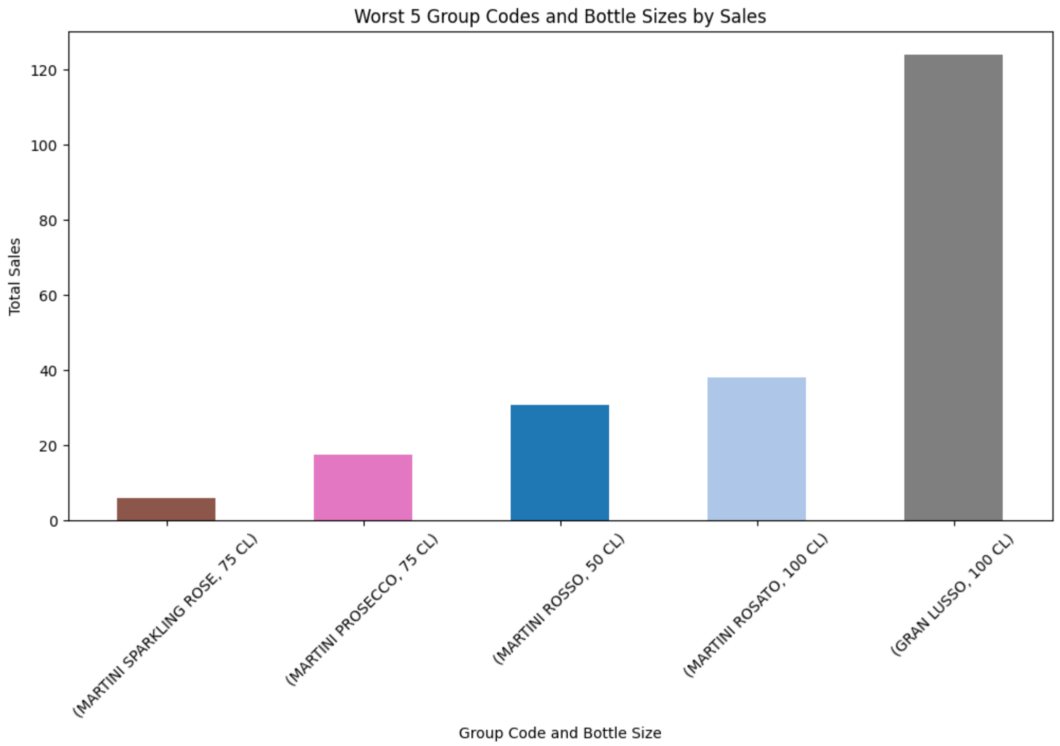


Figure 2 - Worst 5 SKU

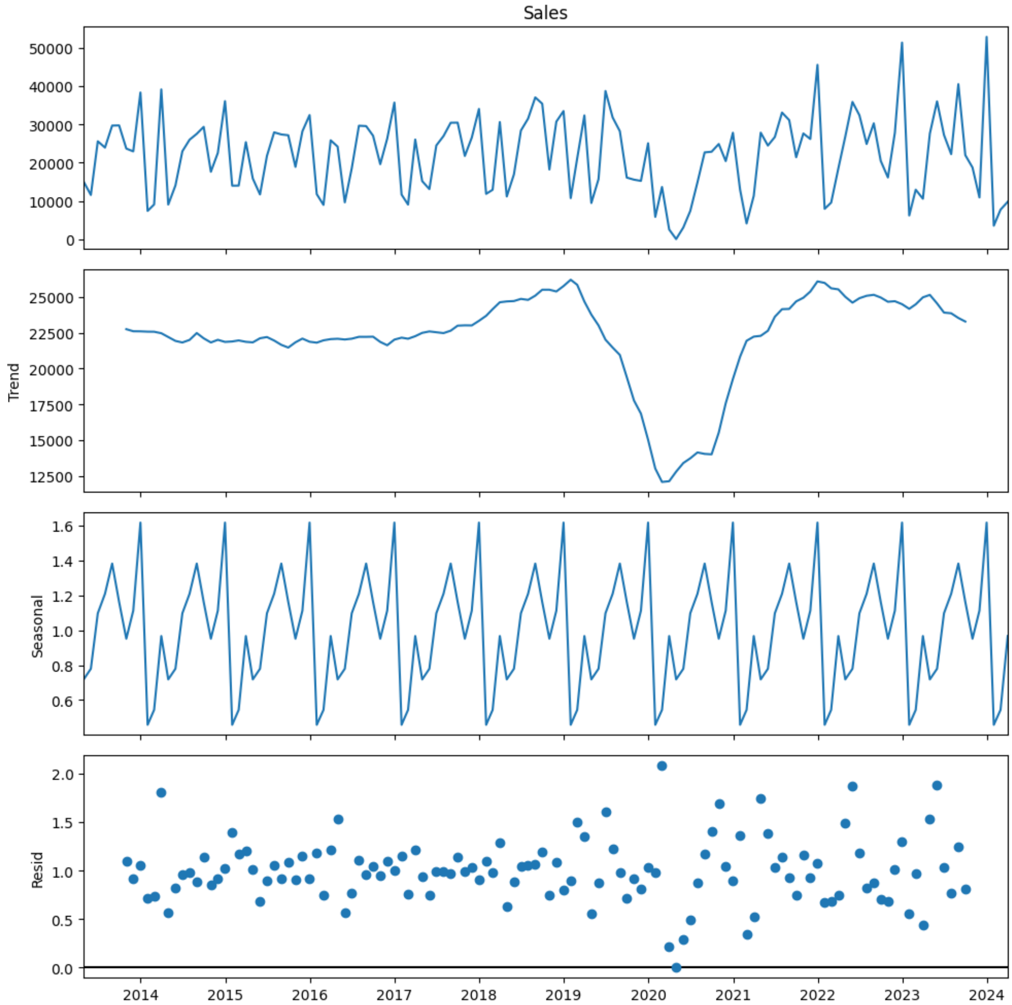


Figure 3 Time Series Decomposition Sales

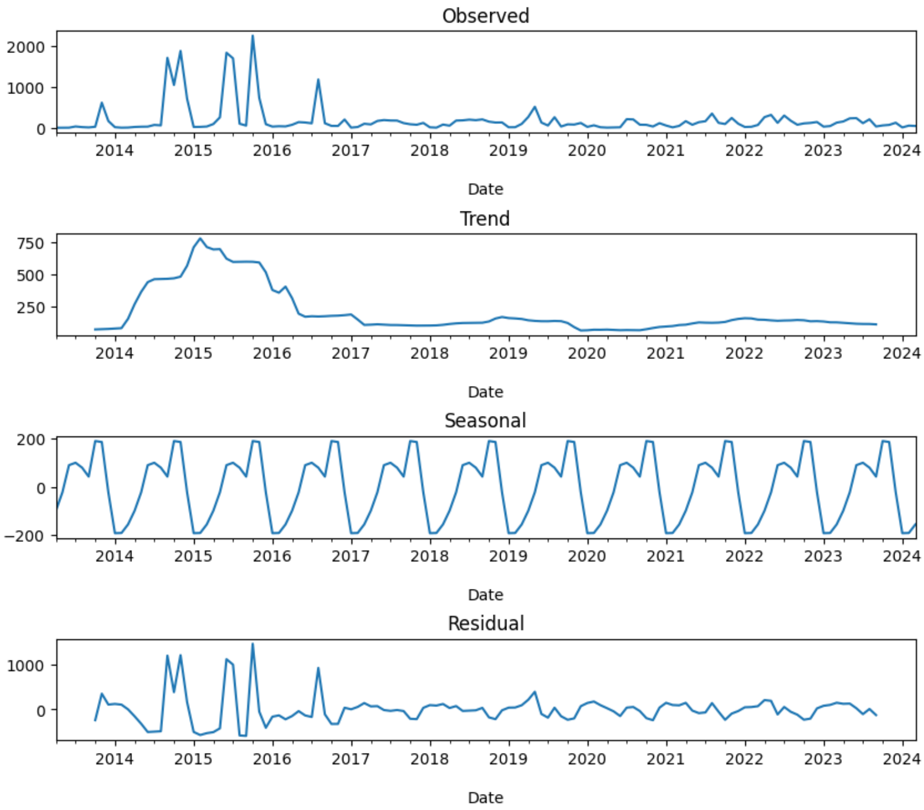


Figure 4- Times Serie Asti Martini 75CL

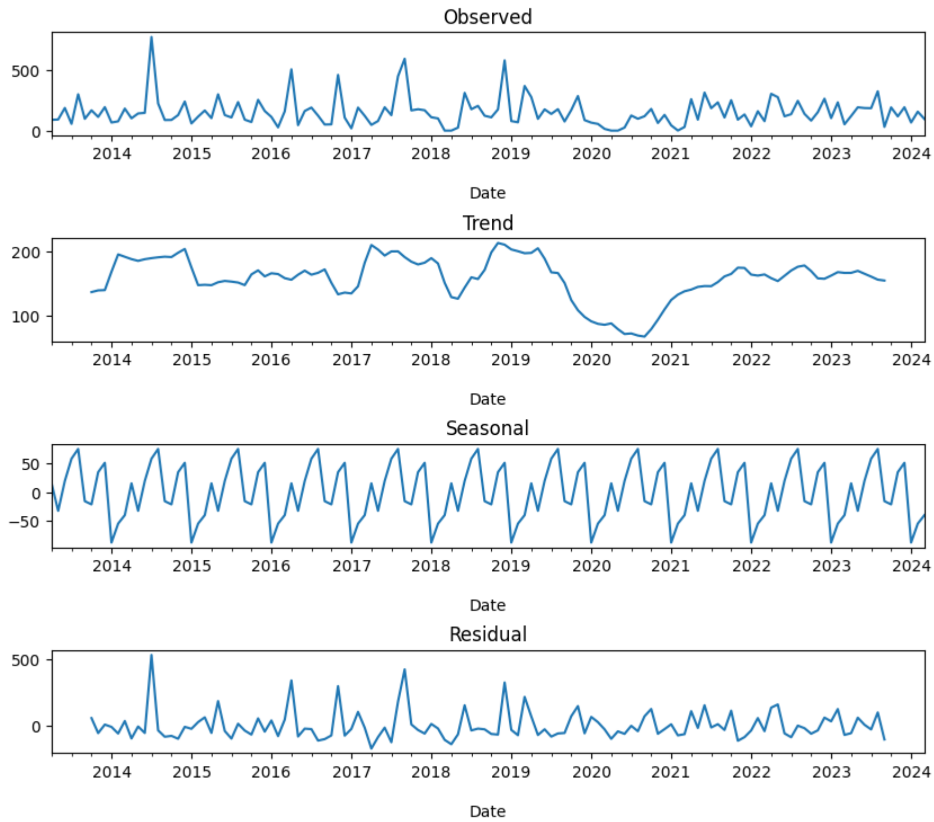


Figure 5 - Time Series *Martini Bianco 6CL*

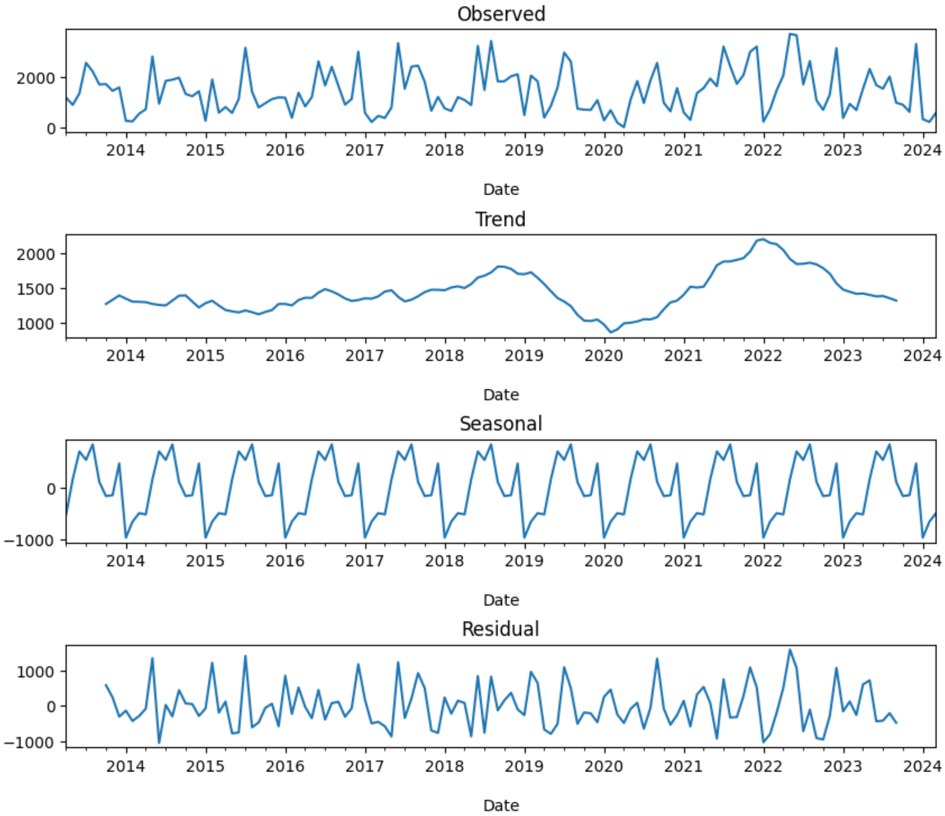


Figure 6 - Time Series Martini Bianco 100CL

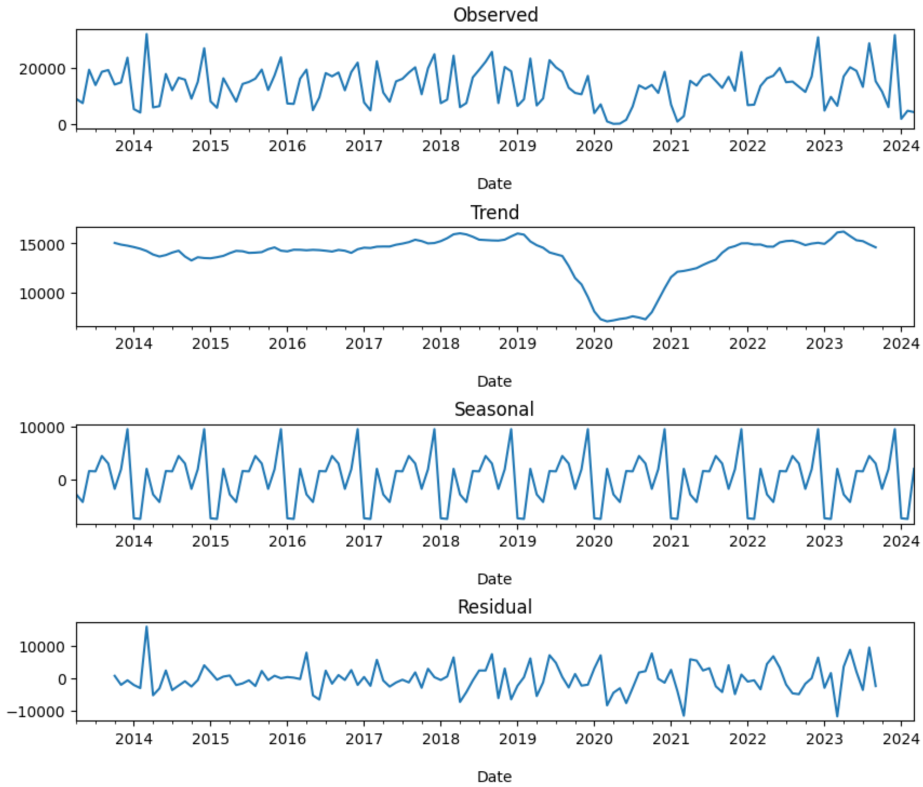


Figure 7 - Time Series Martini Rosso 6CL

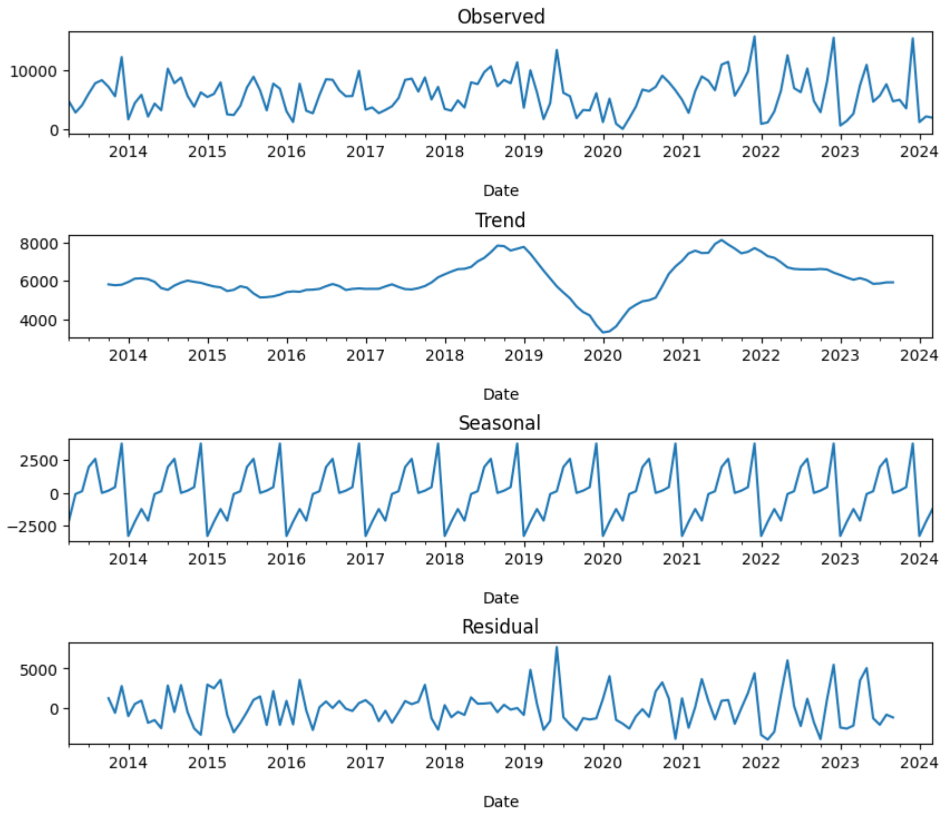


Figure 8 - Time Series Martini Rosso 100CL

Dataset	Outliers (Date)	Residual Value
Asti Martini 75CL	2014-09-01	1201.91
	2014-11-01	1211.71
	2015-06-01	1122.64
	2015-10-01	1467.10
Martini Bianco 6CL	2014-07-01	531.43
	2016-04-01	338.65
	2017-09-01	422.47
Martini Rosso 100CL	2019-06-01	7706.02
Martini Rosso 6CL	2014-03-01	15999.89
Martini Bianco 100CL	No significant outliers	-

Figure 9 - SKUs's data set and their outliers

Time Series	ADF Statistic	p-value	Result
Unemployment	-1.0565	0.9360	Non-Stationary
GDP	-1.7107	0.7462	Non-Stationary
Overnight Stays	-2.6703	0.2486	Non-Stationary

Figure 10 - ADF Results of the External Variables

Time Series	ADF Statistic	p-value	Result
Unemployment	-3.074	1.07e-10	Stationary
GDP	-11.76	0.0	Stationary
Overnight Stays	-2.56	1.07e-10	Stationary

Figure 11 - ADF Results Variable Externals after diff

Time Series	ADF Statistic	p-value	Result
Asti Martini 75CL	-1.1317	0.2343	Non-Stationary
Martini Bianco 6CL	-0.6981	0.4134	Non-Stationary
Martini Rosso 100CL	-0.3752	0.5466	Non-Stationary
Martini Rosso 6CL	-0.4115	0.5321	Non-Stationary
Martini Bianco 100CL	-0.3588	0.5531	Non-Stationary

Figure 12 - ADF Results TOP 5 SKUs

Time Series	ADF Statistic	p-value	Result
Asti Martini 75CL	-4.3863	1.52e-05	Stationary
Martini Bianco 6CL	-7.3728	8.77e-12	Stationary
Martini Rosso 100CL	-4.3308	1.92e-05	Stationary
Martini Rosso 6CL	-4.1906	3.42e-05	Stationary
Martini Bianco 100CL	-4.1152	4.63e-05	Stationary

Figure 13 - ADF Results TOP 5 SKUs after diff

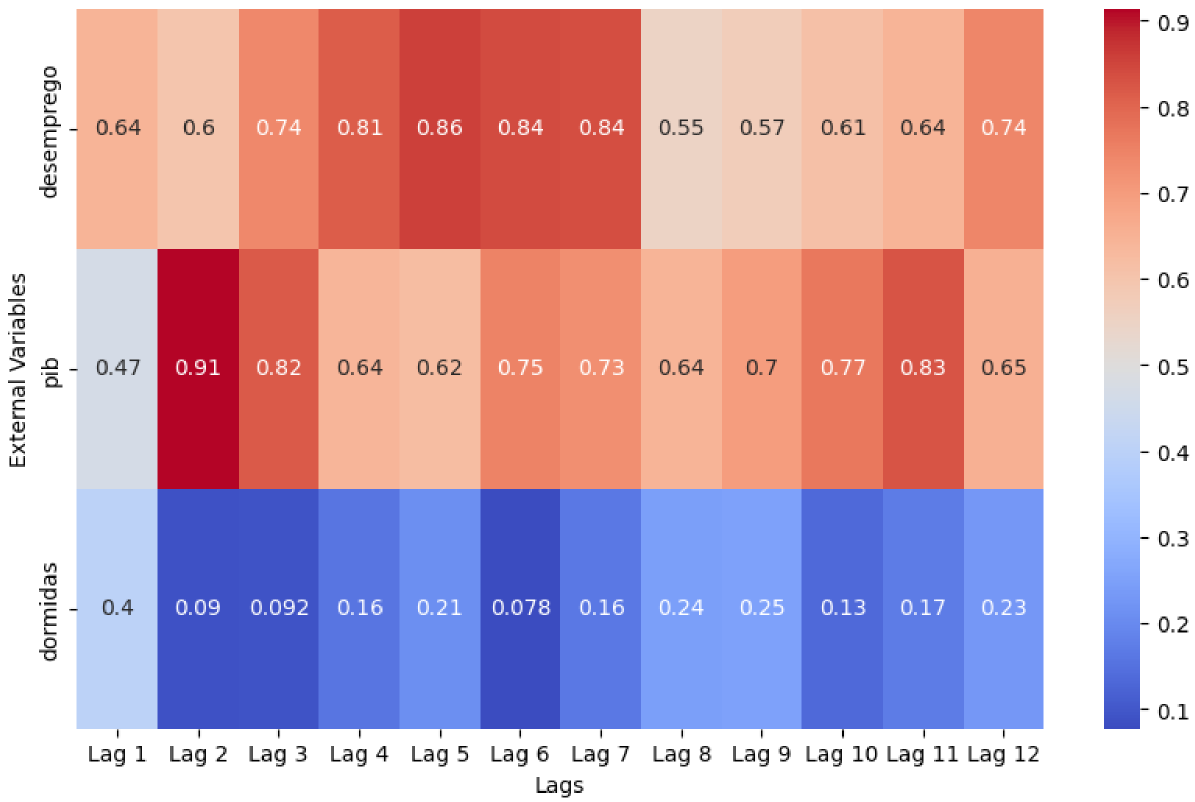


Figure 14 - Heat Map Drink Martini Bianco 6CL (95-5 split)

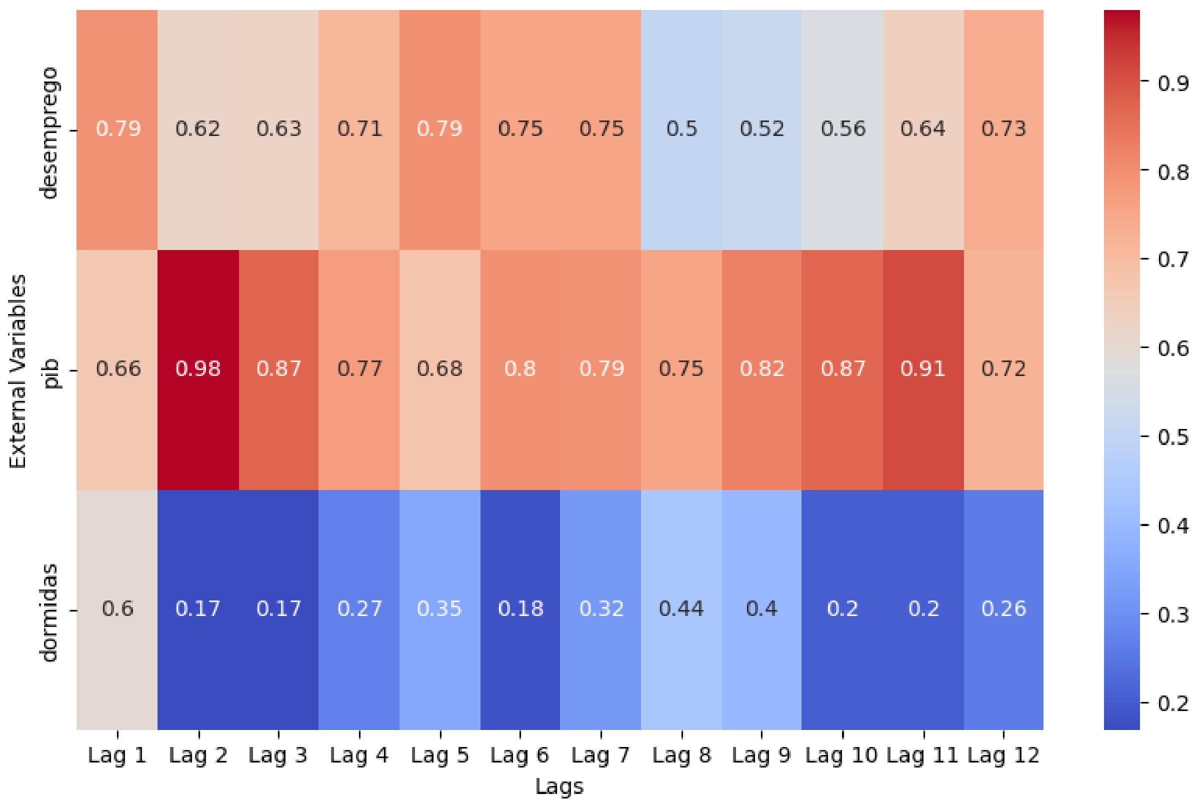


Figure 15 - Heat Map Drink Martini Bianco 6CL (90-10 split)

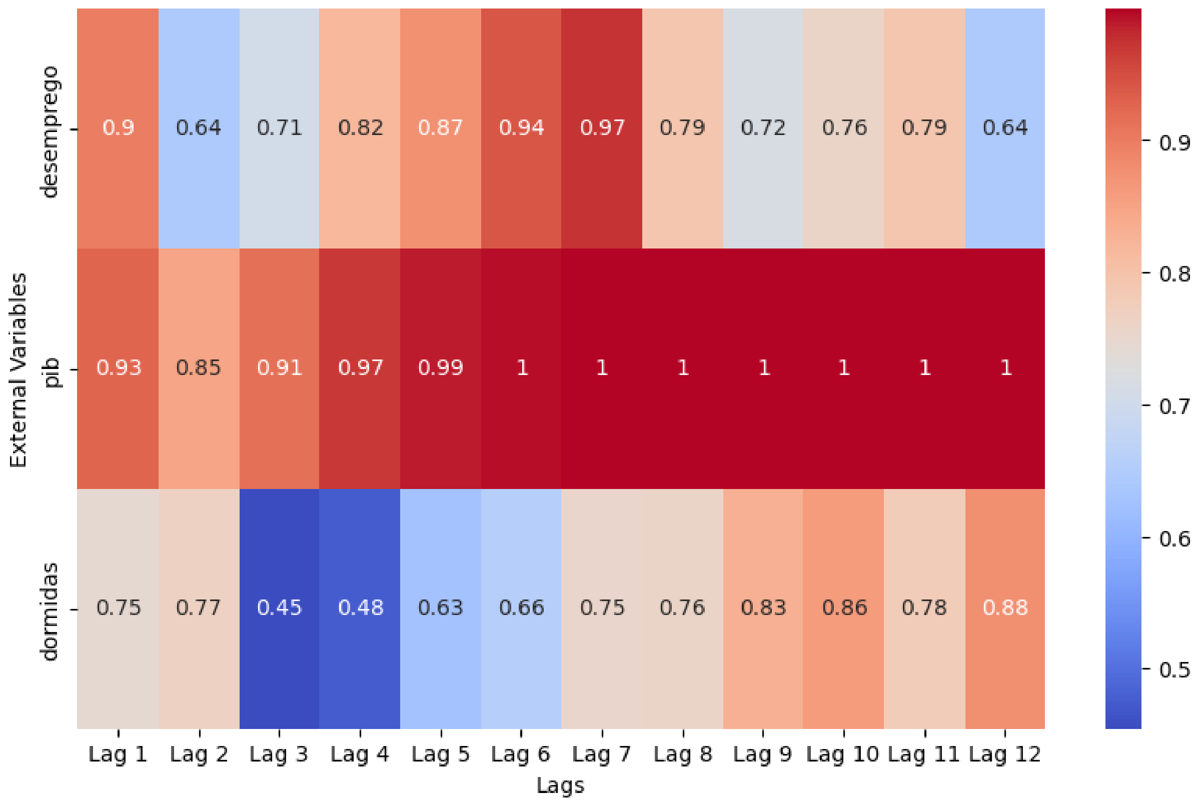


Figure 16 - Heat Map Asti Martini 75CL (95-5 split)

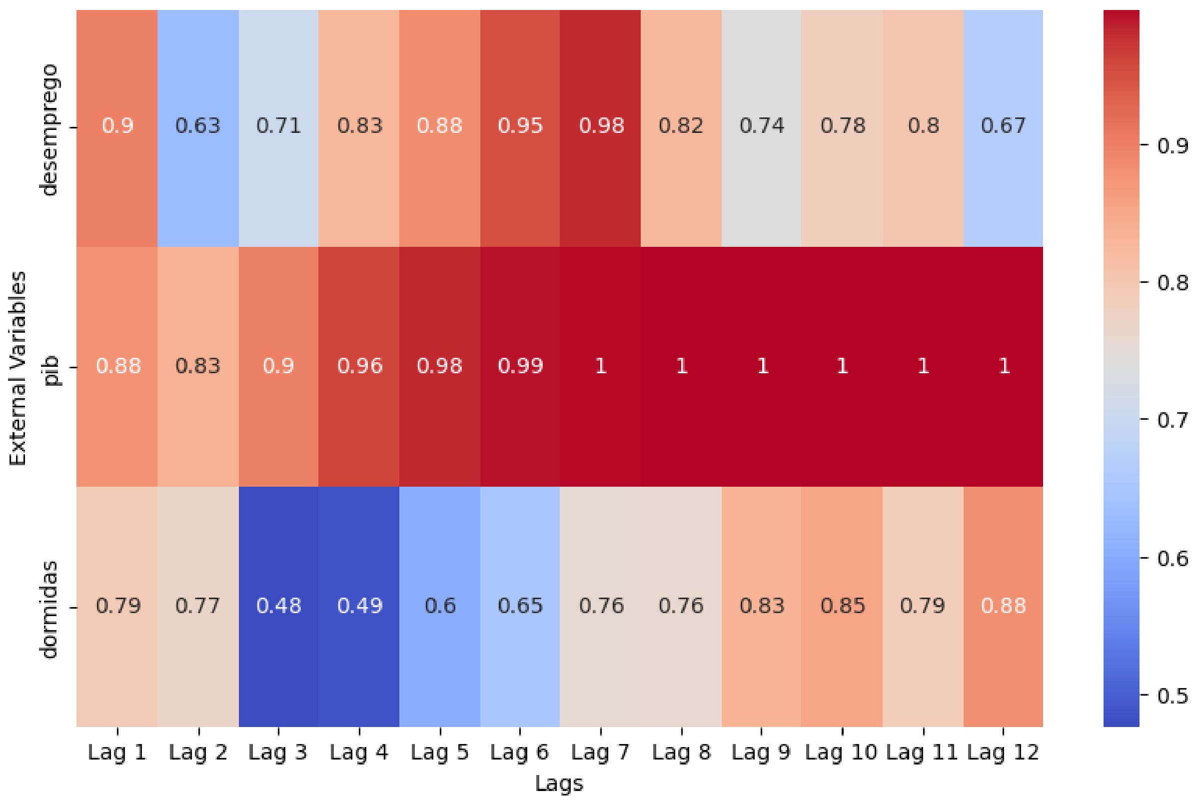


Figure 17 - Heat Map Asti Martini 75CL (90-10 split)

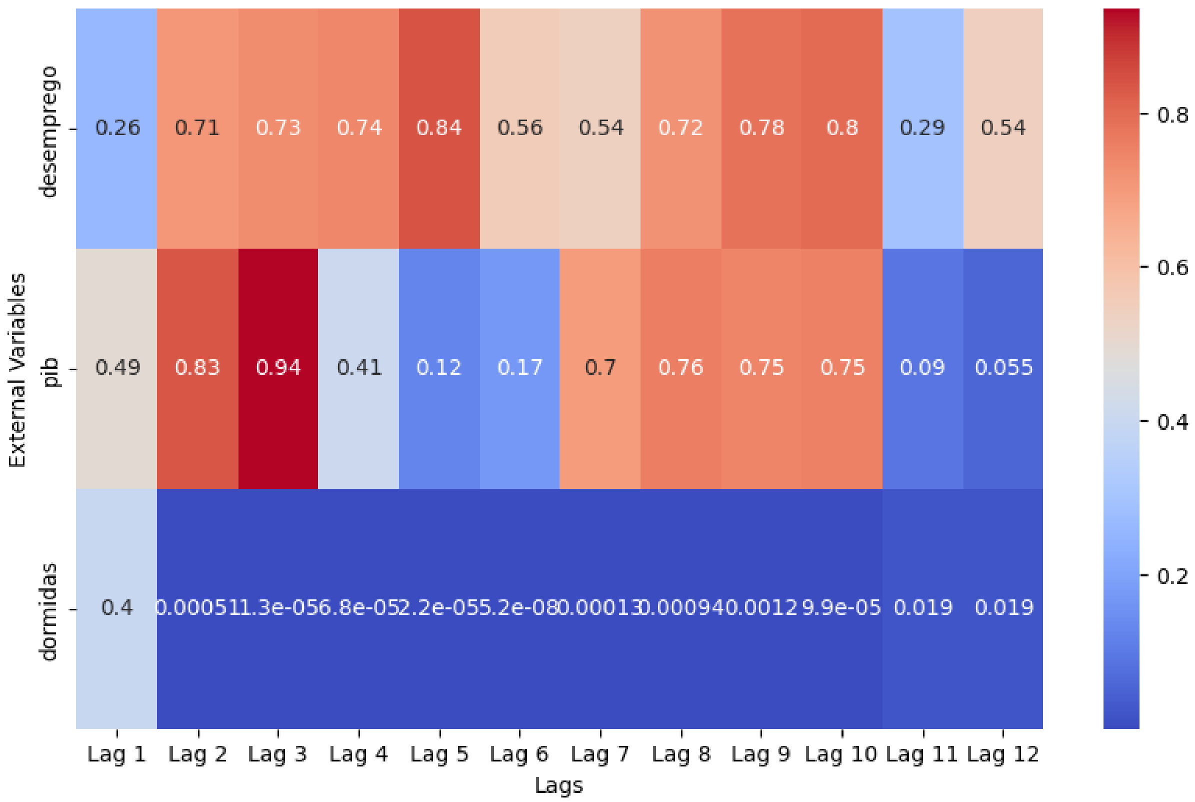


Figure 18 - Heat Map Drink Martini Rosso 6CL (95-5 split)

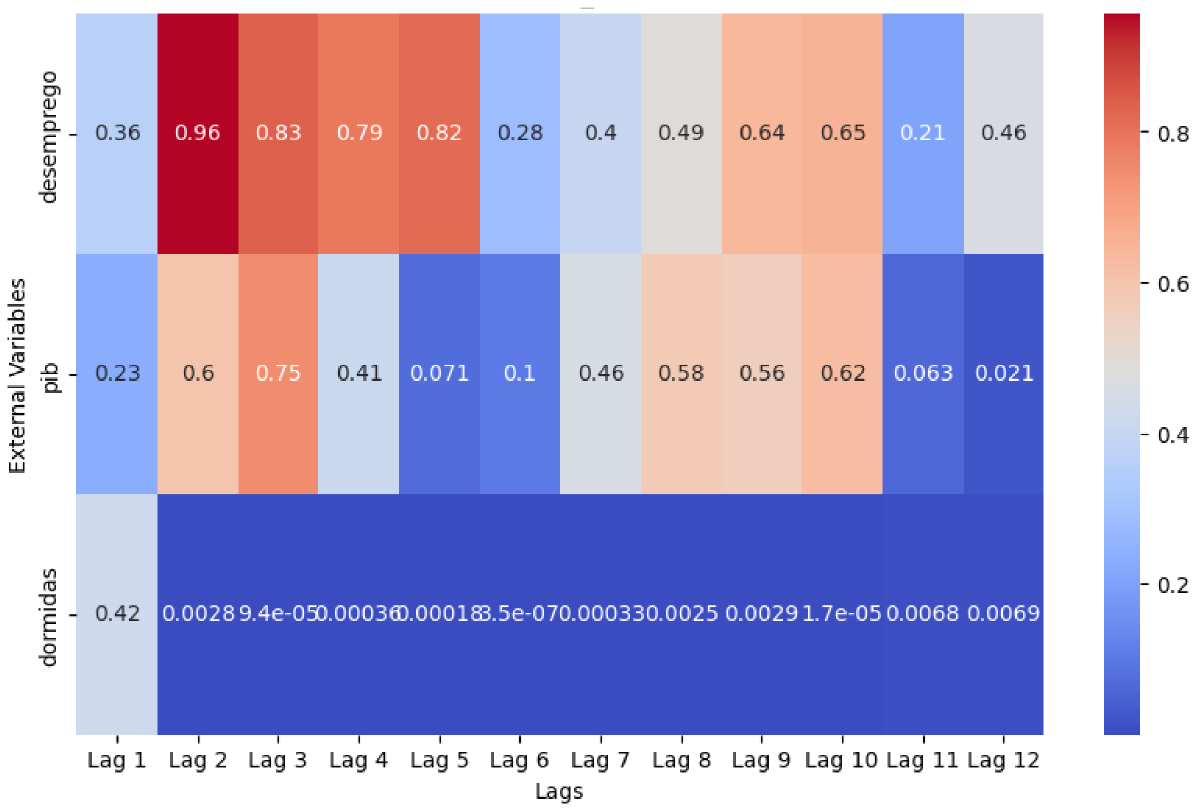


Figure 19 - Heat Map Martini Rosso 6CL (90-10 split)

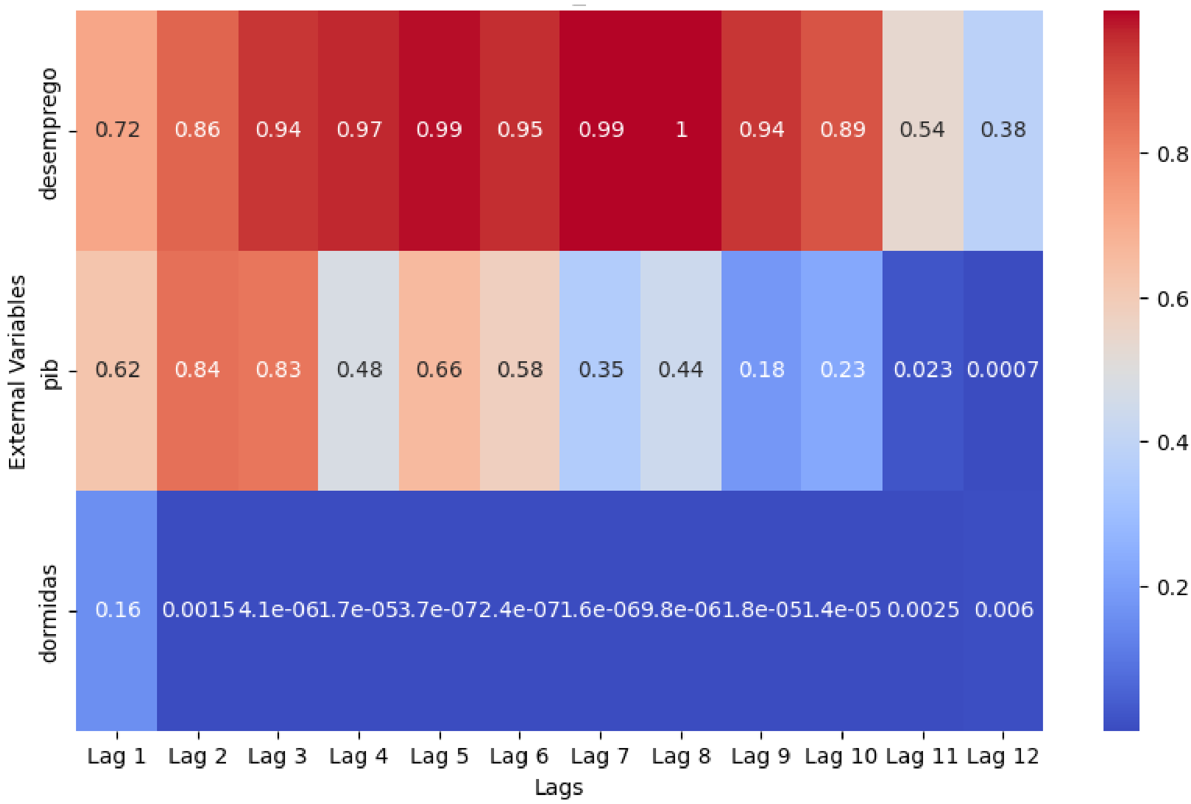


Figure 20 - Heat Map Drink Martini Rosso 100CL (95-5 split)

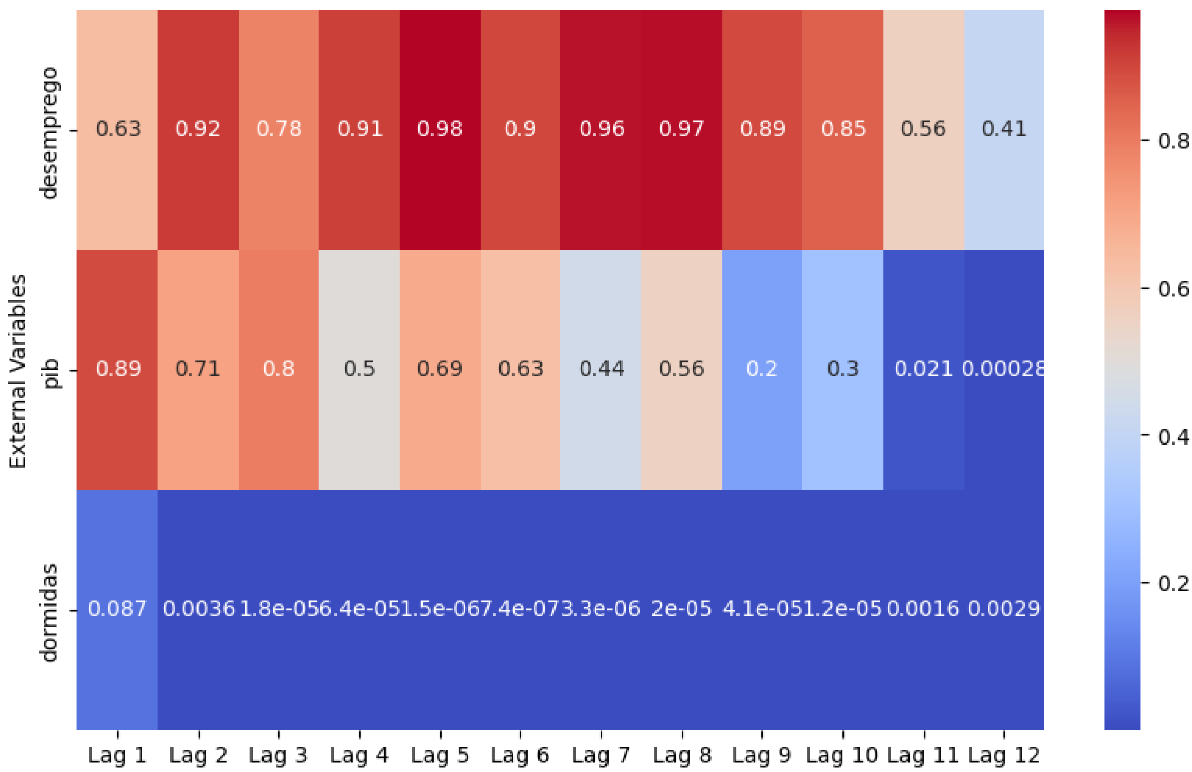


Figure 21 - Heat Map Drink Martini Rosso 100CL (90-10 split)

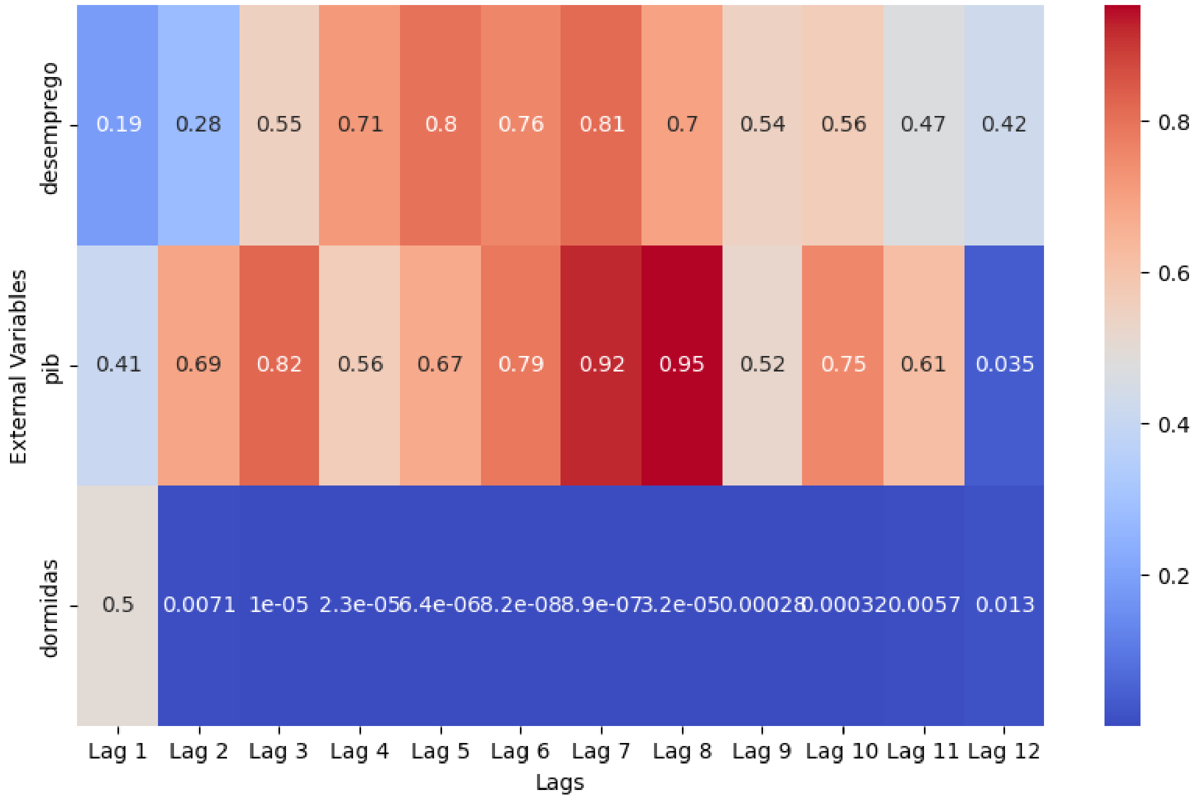


Figure 22 - Heat Map Drink Martini Bianco 100CL (95-5 split)

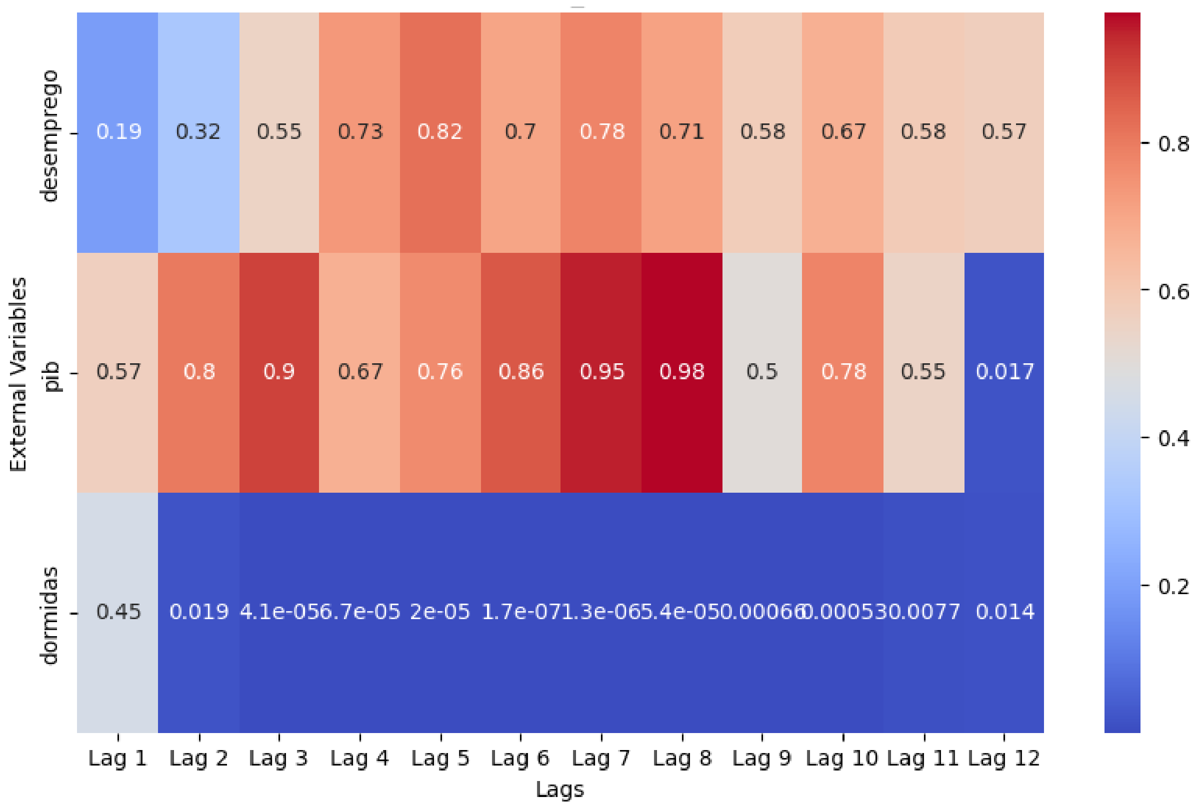


Figure 23 - Heat Map Drink Martini Bianco 100CL (90-5 split)

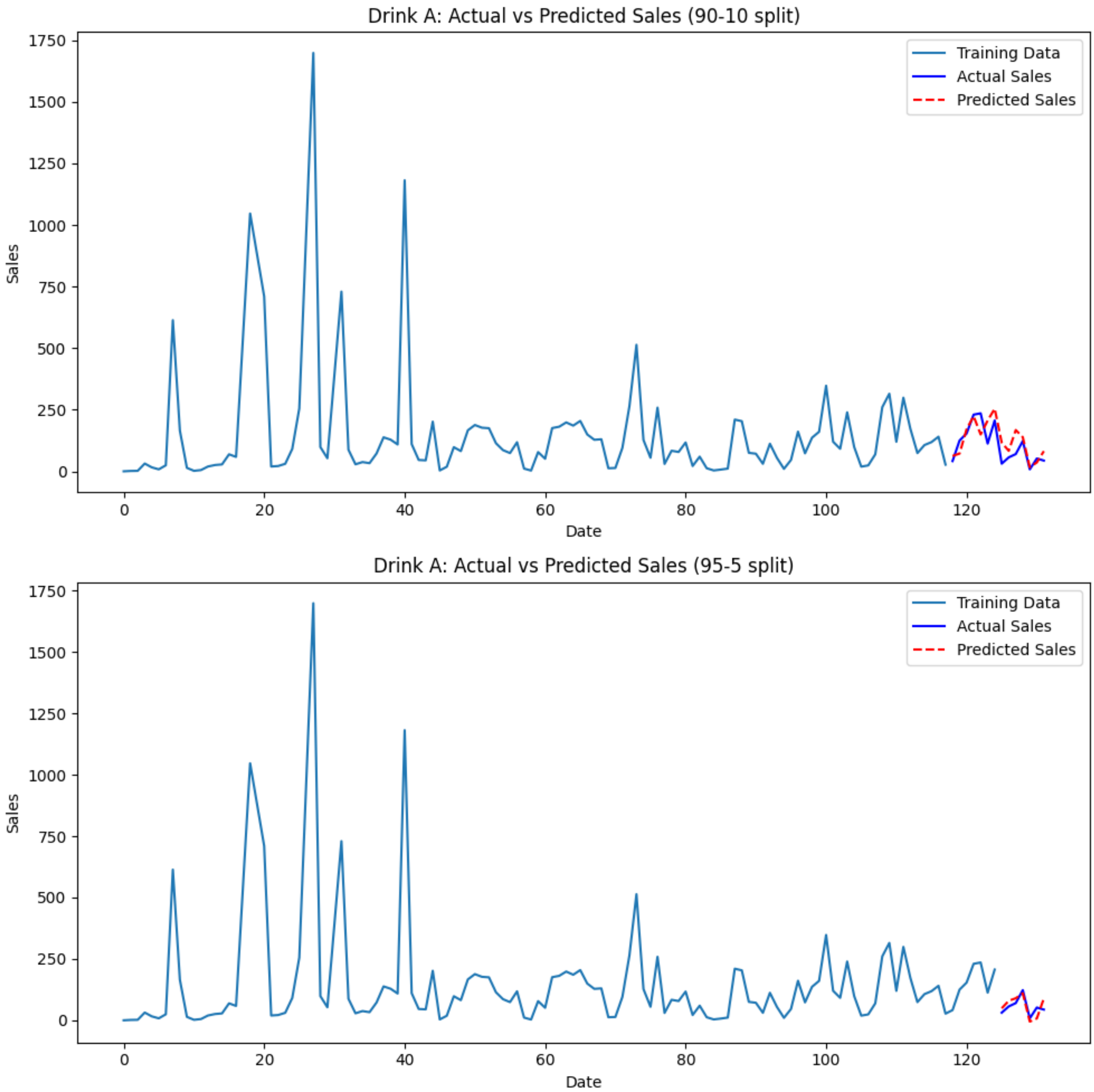
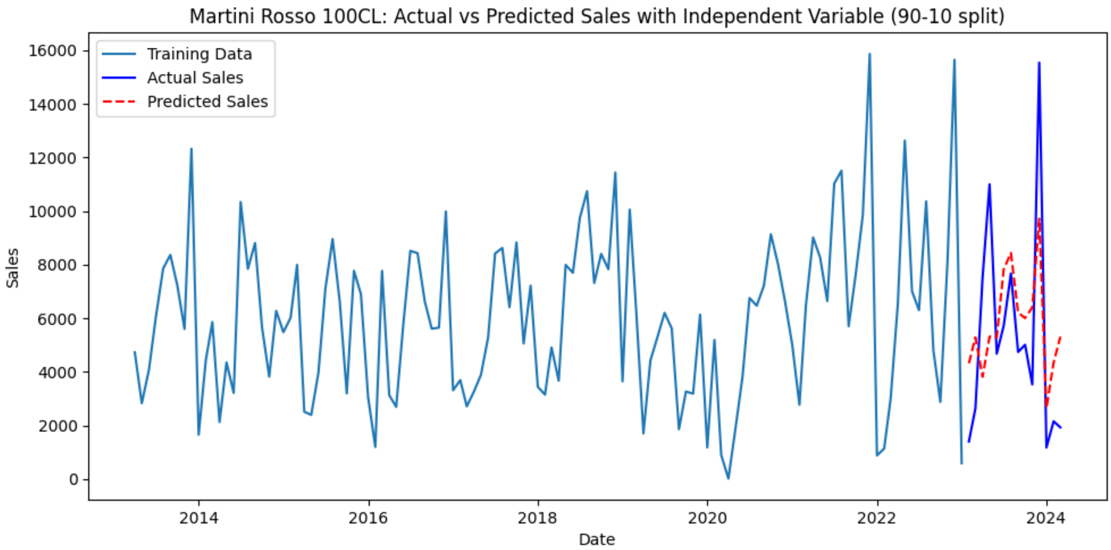


Figure 24 - Actual vs Prediction Sales – Asti Martini 75CL (SARIMAX)



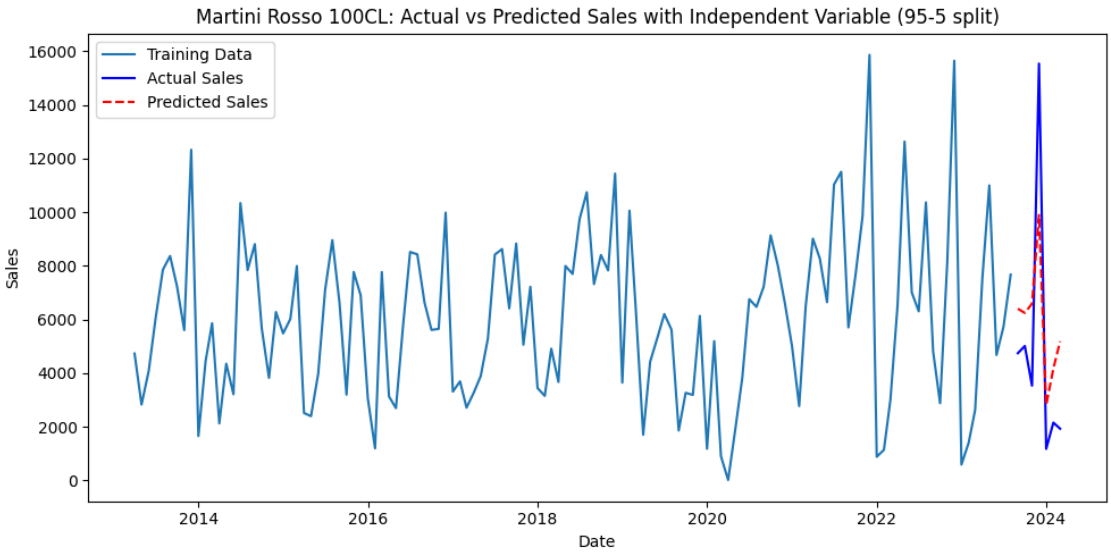


Figure 25 - Actual vs Predicted Sales - Martini Rosso 100CL (Prophet)

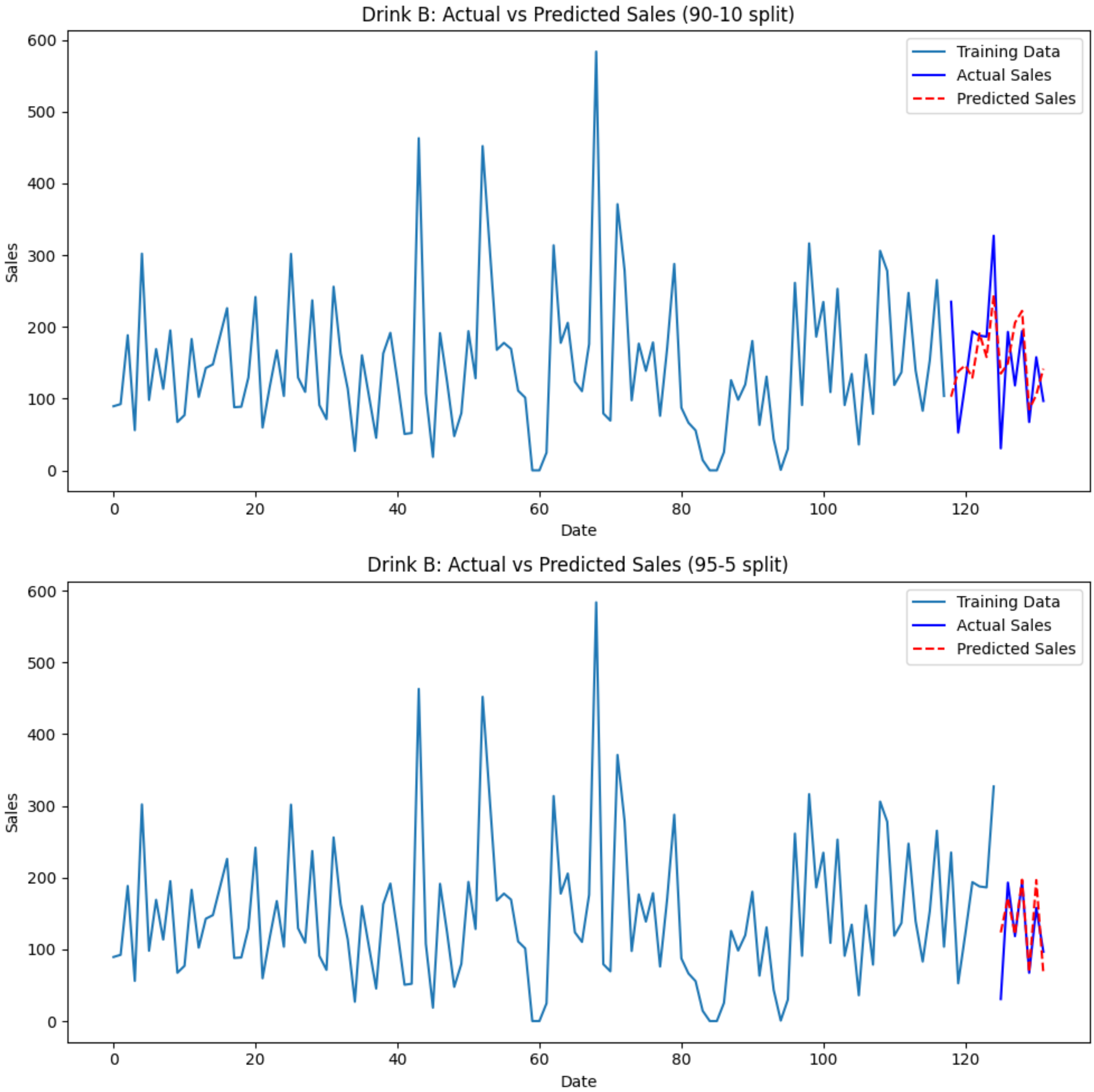


Figure 26 - Actual vs Predicted Sales - Martini Bianco 6CL (SARIMAX)

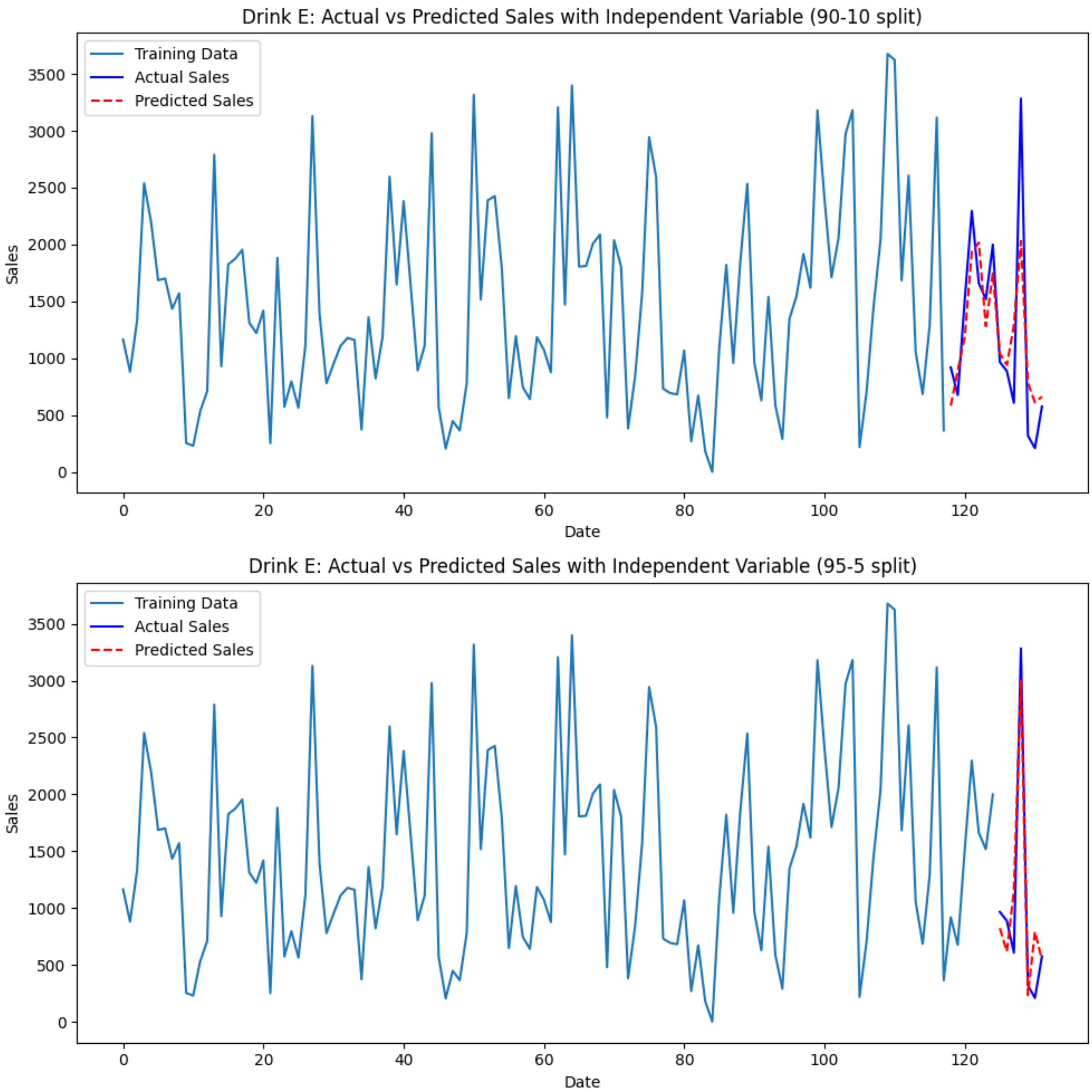
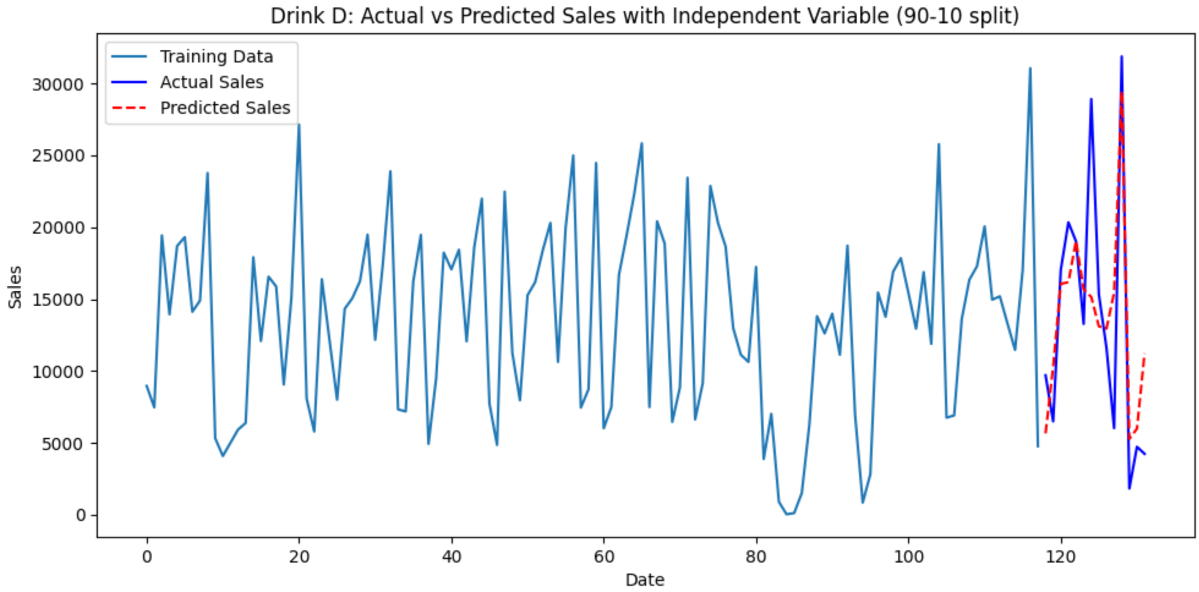


Figure 27 - Actual vs Predicted Sales - Martini Bianco 100CL (SARIMAX)



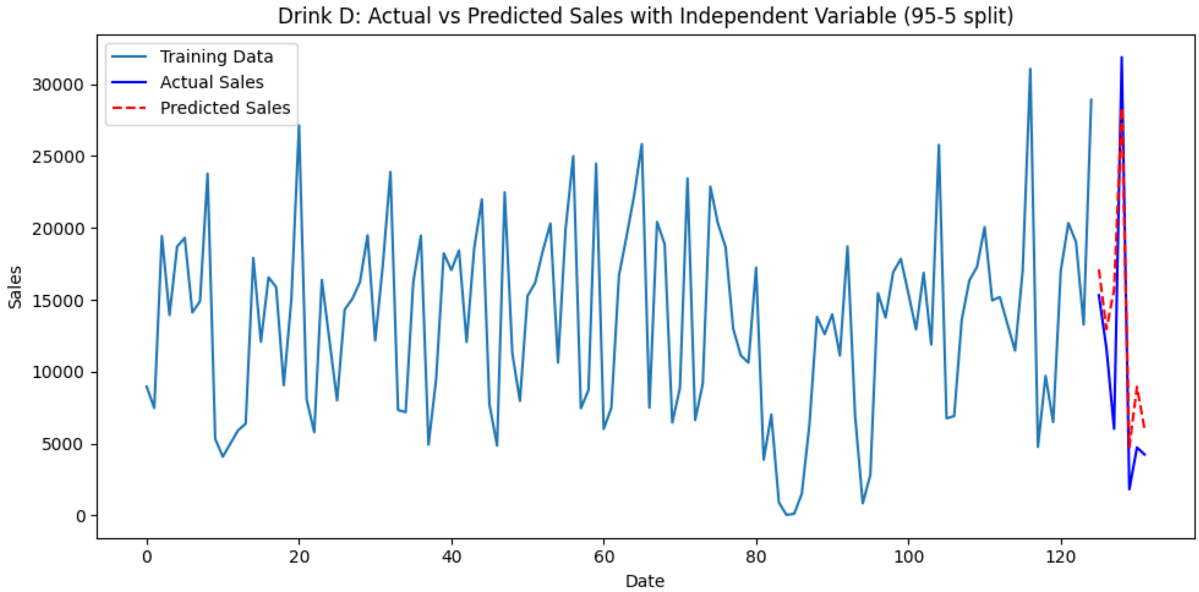


Figure 28 - Actual vs Predicted Sales - Martini Rosso 6CL (SARIMAX)

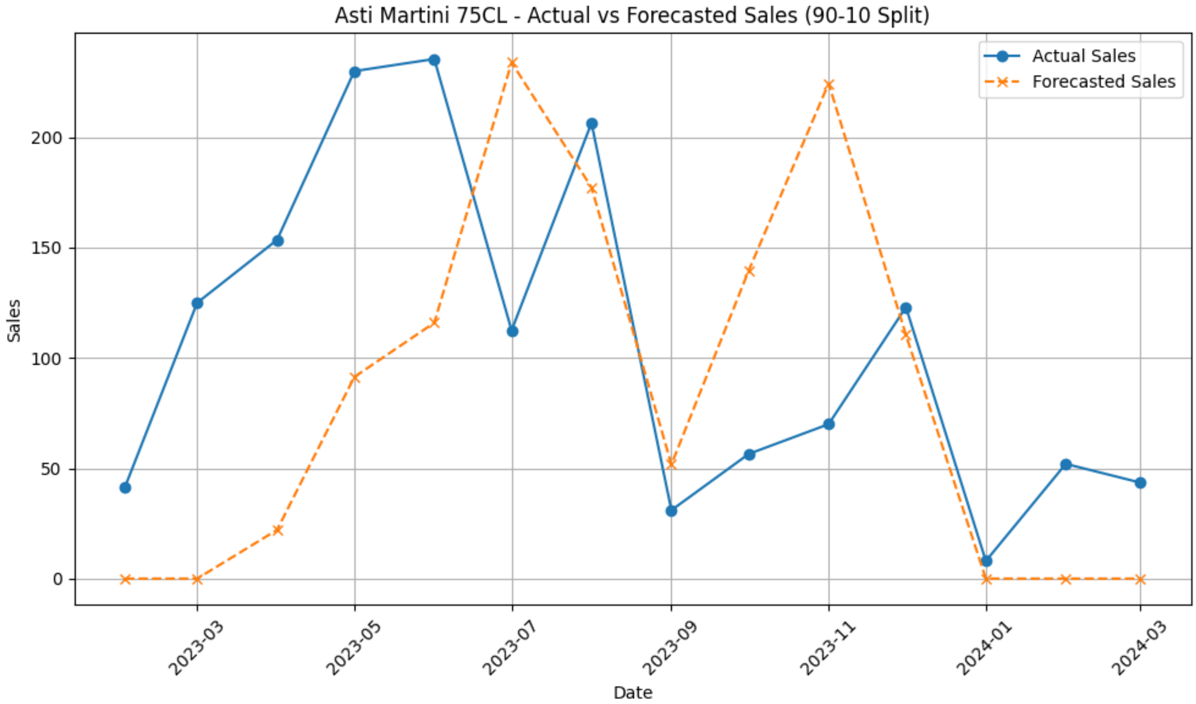


Figure 29 - Actual vs Forecast values on test data set 90-10 split for the Asti Martini 75CL

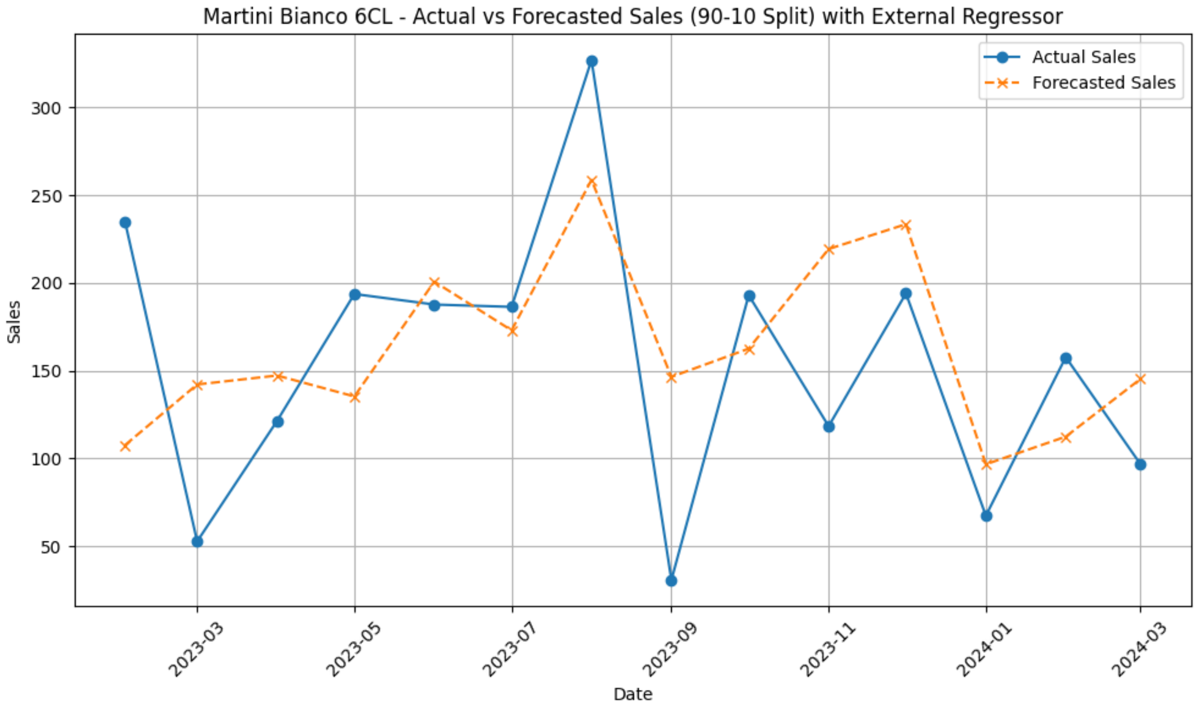


Figure 30 - Actual vs Forecast values on test data set 90-10 split for the SKU Martini Bianco 6CL

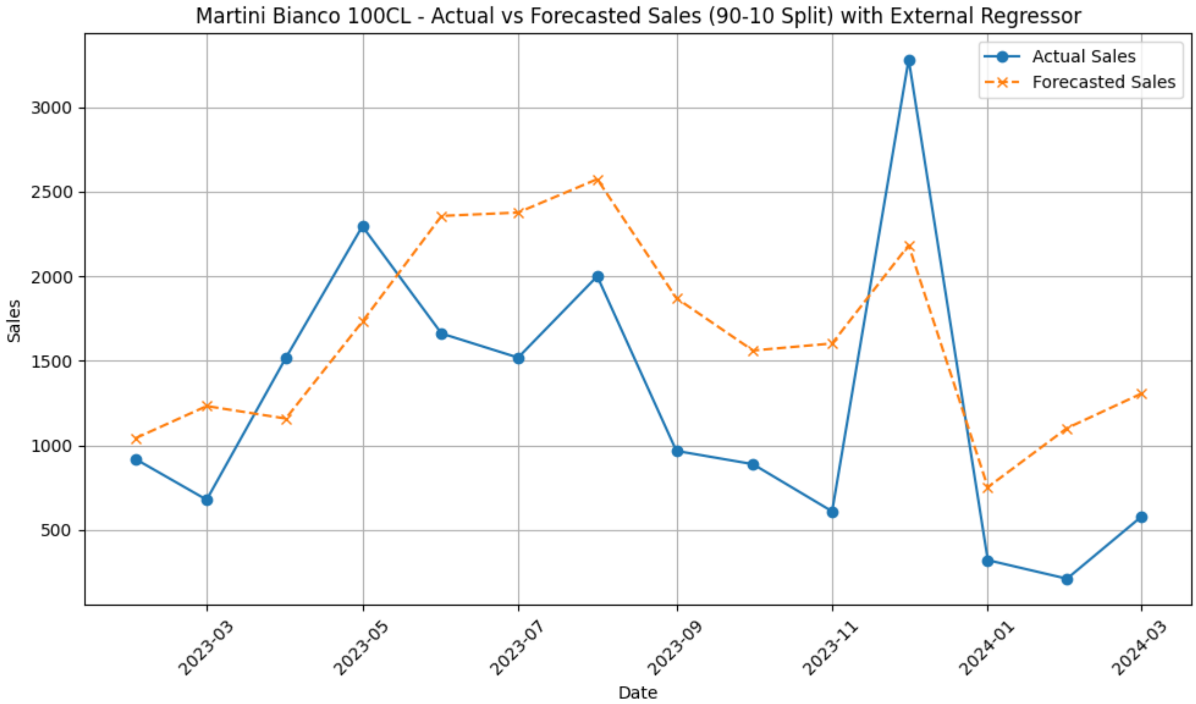


Figure 31 - Actual vs Forecast values on test data set 90-10 split for the SKU Martini Bianco 100CL

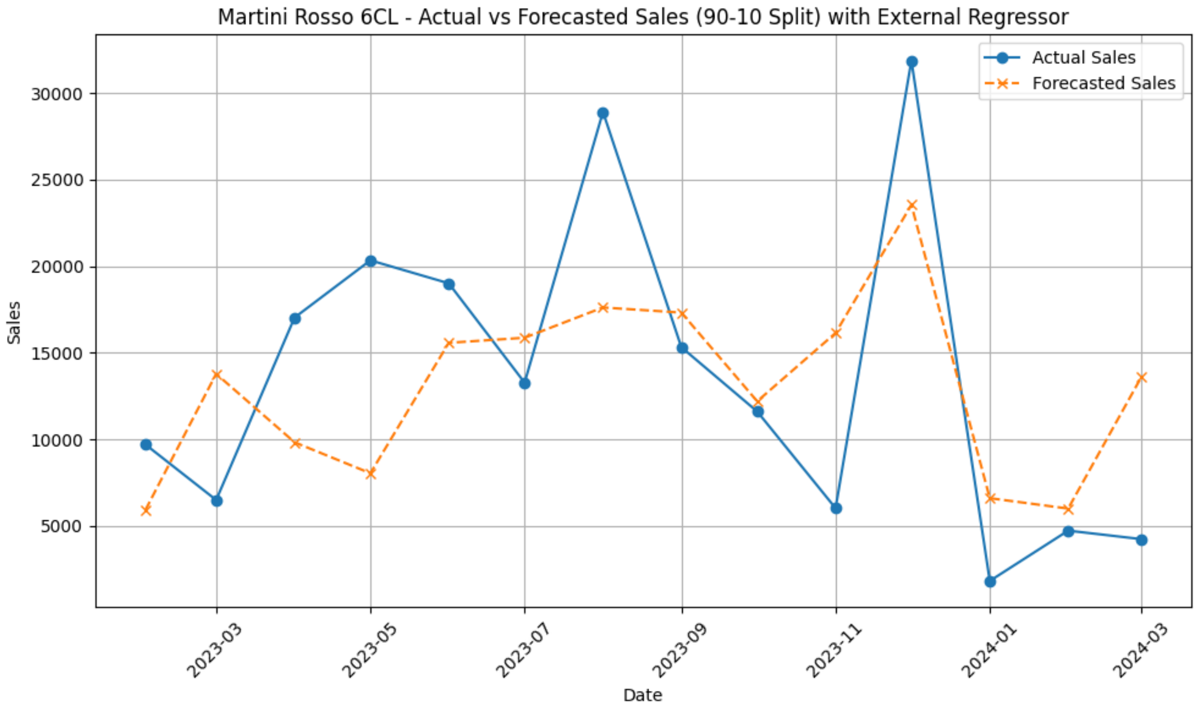


Figure 32 - Actual vs Forecast values on test data set 90-10 split for the SKU Martini Rosso 6CL

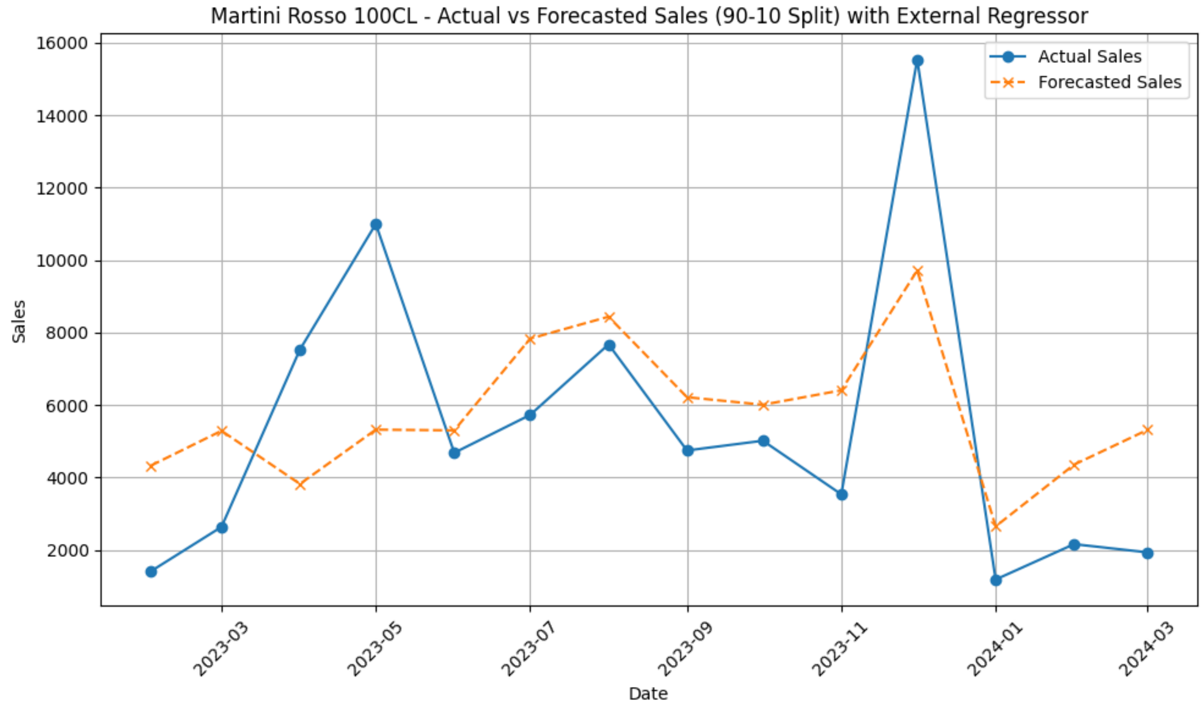


Figure 33 - Actual vs Forecast values on test data set 90-10 split for the SKU Martini Rosso 100CL

Drink	Split	AIC	RMSE	Best Order
Asti Martini 75CL	90-10	1307.47	54.55	(2, 0, 2) x (1, 1, 0, 12)
	95-5	1588.28	28.42	(0, 0, 2) x (0, 1, 0, 12)
Martini Bianco 6CL	90-10	1142.39	64.64	(0, 1, 1) x (0, 1, 1, 12)
	95-5	1263.22	43.58	(0, 0, 0) x (1, 1, 0, 12)
Martini Rosso 100CL	90-10	1766.53	1514.94	(0, 2, 1) x (1, 1, 0, 12)
	95-5	1832.66	1833.79	(0, 1, 1) x (1, 1, 1, 12)
Martini Rosso 6CL	90-10	1848.04	5403.03	(2, 0, 0) x (1, 1, 0, 12)
	95-5	2291.64	4490.92	(0, 0, 2) x (1, 0, 0, 12)
Martini Bianco 100CL	90-10	1720.70	468.34	(2, 0, 1) x (1, 0, 0, 12)
	95-5	1848.41	340.73	(2, 0, 2) x (0, 1, 0, 12)

Figure 34 - AIC, RMSE, and Best Order Results for SARIMAX Predictions

SKU	Mean	Std Dev	Min	Max
Asti Martini 75CL	195.2	378.8	0.0	2255.0
Martini Bianco 6CL	155.9	121.7	0.0	778.3
Martini Rosso 100CL	5997.4	3248.4	20.7	15859.3
Martini Rosso 6CL	13699.1	6999.0	28.7	32230.5
Martini Bianco 100CL	1428.5	878.7	2.0	3676.7

Figure 35 - Descriptive Statistics for Top 5 SKUs