



HELLENIC OPEN UNIVERSITY
SCHOOL OF SOCIAL SCIENCES

Supply Chain Management (SCM)

Analyzing and Forecasting Sales Patterns in Craft Beer
Production: A Time Series Approach

Vasiliki Vakouftsi

Supervisor: Nikolaos Thomaidis

Patras, Greece, March 2025

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Analyzing and Forecasting Sales Patterns in Craft Beer Production: A Time Series Approach

Vasiliki Vakouftsi

Supervising Committee

Supervisor:

Nikolaos Thomaidis

Associate Professor

Department of Financial and Management

Engineering

University of the Aegean

Patras, Greece, March 2025

This dissertation is dedicated to my family....

Abstract

In today's rapidly evolving market, the craft beer industry faces unique challenges in understanding and forecasting product demand. Influenced by a variety of internal and external factors, the demand for craft beer products requires accurate forecasting to optimize production, manage supply chains effectively and meet customer expectations. Key elements such as ingredient sourcing, seasonal workforce management and the dynamic nature of consumer preferences make the development of advanced forecasting techniques essential. Precise sales predictions not only improve operational efficiency but also provide a competitive edge, supporting business growth and enhancing strategic decision-making.

The craft beer industry in Greece, like many others, has been significantly impacted by external disruptions, including the Covid-19 pandemic. This global crisis altered consumption patterns, with shifts in consumer behavior affecting demand across various beer categories. The need for improved forecasting methods has become critical to navigate these changes and ensure stability in production and supply chain operations.

The objective of this dissertation is to explore and analyze the sales patterns of eight craft beer products distributed across Greece by a local brewery. The study examines the statistical features of these products' time series, their behavior over a four-year period from 2020 to 2023 and the impact of seasonal trends and the Covid-19 pandemic. Employing regression analysis and Exponential Weighted Moving Average (EWMA) forecasting models, the research aims to identify robust prediction tools. By evaluating the accuracy of these models, the goal is to determine the most effective forecasting approach that aligns with the actual sales data throughout the analysis period.

Keywords

Time series analysis, sales forecasting, craft beer, forecasting methods, prediction accuracy measures

Ανάλυση και Πρόβλεψη Προτύπων Πωλήσεων στην Παραγωγή Χειροποίητης Μπύρας: Μια Προσέγγιση Χρονοσειρών

Βασιλική Βακουφτσή

Περίληψη

Σε μια εποχή που η αγορά εξελίσσεται ραγδαία, η βιομηχανία της χειροποίητης μπύρας αντιμετωπίζει μοναδικές προκλήσεις στην κατανόηση και πρόβλεψη της ζήτησης των προϊόντων. Υπό την επίδραση ποικίλων εσωτερικών και εξωτερικών παραγόντων, η ζήτηση για προϊόντα χειροποίητης μπύρας απαιτεί ακριβείς προβλέψεις για τη βέλτιστη παραγωγή, τη διαχείριση της εφοδιαστικής αλυσίδας και την ικανοποίηση των προσδοκιών των πελατών. Σημαντικά στοιχεία όπως η προμήθεια συστατικών, η διαχείριση εποχιακού εργατικού δυναμικού και η δυναμική φύση των προτιμήσεων των καταναλωτών καθιστούν απαραίτητη την ανάπτυξη προηγμένων τεχνικών πρόβλεψης. Οι ακριβείς προβλέψεις πωλήσεων όχι μόνο βελτιώνουν την επιχειρησιακή απόδοση, αλλά παρέχουν επίσης ένα ανταγωνιστικό πλεονέκτημα, υποστηρίζοντας την επιχειρηματική ανάπτυξη και βελτιώνοντας τη στρατηγική λήψη αποφάσεων.

Η βιομηχανία χειροποίητης μπύρας στην Ελλάδα, όπως και πολλές άλλες, έχει επηρεαστεί σημαντικά από εξωτερικές διαταραχές, συμπεριλαμβανομένης της πανδημίας του Covid-19. Αυτή η παγκόσμια κρίση άλλαξε τα πρότυπα κατανάλωσης, με μεταβολές στη συμπεριφορά των καταναλωτών να επηρεάζουν τη ζήτηση σε διάφορες κατηγορίες μπύρας. Η ανάγκη για βελτιωμένες μεθόδους πρόβλεψης έχει γίνει κρίσιμη για την αντιμετώπιση αυτών των αλλαγών και τη διασφάλιση της σταθερότητας στην παραγωγή και τις λειτουργίες της εφοδιαστικής αλυσίδας.

Στόχος αυτής της διατριβής είναι να διερευνήσει και να αναλύσει τα πρότυπα πωλήσεων οκτώ προϊόντων χειροποίητης μπύρας που διανέμονται σε όλη την Ελλάδα από μια τοπική ζυθοποιία. Η μελέτη εξετάζει τα στατιστικά χαρακτηριστικά των χρονοσειρών αυτών των προϊόντων, τη συμπεριφορά τους κατά τη διάρκεια μιας τετραετούς περιόδου από το 2020 έως το 2023 και τον αντίκτυπο των εποχιακών τάσεων και της πανδημίας του Covid-19.

Χρησιμοποιώντας ανάλυση παλινδρόμησης και μοντέλα πρόβλεψης κινητού μέσου όρου
Postgraduate Dissertation

εκθετικής εξομάλυνσης, η έρευνα στοχεύει στον εντοπισμό αξιόπιστων εργαλείων πρόβλεψης. Αξιολογώντας την ακρίβεια αυτών των μοντέλων, ο στόχος είναι να καθοριστεί η πιο αποτελεσματική προσέγγιση πρόβλεψης που ευθυγραμμίζεται με τα πραγματικά δεδομένα πωλήσεων κατά τη διάρκεια της περιόδου ανάλυσης.

Λέξεις – Κλειδιά

Ανάλυση χρονοσειρών, πρόβλεψη πωλήσεων, χειροποίητη μύρα, μέθοδοι πρόβλεψης, μέτρα ακρίβειας πρόβλεψης

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List of Abbreviations & Acronyms

ACF	Autocorrelation Function
ADF	Augmented Dickey-Fuller
AIC	Akaike Information Criteria
ANN	Artificial Neural Networks
ANOVA	Analysis of Variance
AR	Auto Regressive
ARIMA	Auto Regressive Integrated Moving Average
ARMA	Auto Regressive Moving Average
ARMAX	Auto Regressive Moving Average with eXogenous variable
ARUMA	Auto Regressive Unit Root Moving Average
AutoML	Automated Machine Learning
BATS	<u>B</u> ox-Cox Transformation of the time series with the inclusion of <u>A</u> RMA errors and the inclusion of <u>T</u> rend and <u>S</u> easonal components.
BIC	Bayesian Information Criterion
biLSTM	Bidirectional Long Short-Term Memory Network
CNN	Convolutional Neural Network
ERP	Enterprise Resource Planning
EWMA	Exponential Weighted Moving Average
IPA	India Pale Ale
IQR	Interquartile Range
ISO	International Organization for Standardization
KPSS	Kwiatkowski-Phillips-Schmidt-Shin test
LBQ	Ljung-Box Q statistic test
LSTM	Long Short-Term Memory Network
MAD	Mean Absolute Deviation
MAE	Mean Absolute Error
MAPE	Mean Absolute Percentage Error
ML	Machine Learning
MLP	Multi-Layer Perceptron
MLR	Multiple Linear Regression
MSE	Mean Square Error
OLS	Ordinary Least Square
PACF	Partial Autocorrelation Function
RF	Random Forest
RMSE	Root Mean Square Error

S&OP	Sales and Operational Planning
SARIMA	Seasonal Auto Regressive Integrated Moving Average
SLR	Simple Linear Regression
SSR	Sum of Squared Residuals
USA	United States of America
WHO	World Health Organization

1. The Craft Beer Industry in Greece

In recent years, Greece has emerged as a noteworthy player in the craft beer industry, with significant growth observed from the early 2000s to today. This burgeoning sector reflects the country's rich brewing history while showcasing its ability to innovate and adapt to modern tastes. The rise of local breweries has created a diverse and competitive market that appeals to both domestic consumers and international beer enthusiasts.

1.1 Introduction

The production of craft beer in Greece is a year-round endeavor, with distinct peaks in production correlating with seasonal demand and tourism influxes. Key regions contributing to this industry include Athens, Thessaloniki, Crete and the Cyclades, each hosting a variety of breweries that produce unique beer styles.



Figure 1, “Craft Beer Brewery Locations in Greece”. Source: <https://www.bonnieandclydeurbantours.com/>

Production planning is a critical phase for breweries in Greece. This involves organizing resources and schedules to meet demand efficiently while addressing challenges like long fermentation times and limited production capacity. Key steps include managing the preparation and bottling processes to ensure smooth operations and avoid delays. Effective planning helps breweries reduce costs, minimize waste and keep up with customer demand, making it essential for their success (Georgiadis et al., 2021).

Concurrently, breweries undergo rigorous quality control processes. Certifications are pursued to ensure high production standards. For instance, Olympic Brewery holds certifications including ISO 9001:2015, ISO 14001:2015, and ISO 45001:2018, reflecting their dedication to quality, environmental management and occupational health and safety (Olympic Brewery S.A., 2025)

1.2 Key Ingredients

As noted by The Hellenic Association of Brewers (2025), Greek craft beer production is built on a balance of tradition and innovation, using four key natural ingredients: water, barley (in the form of malt), hops and yeast. Historically, these ingredients were the only ones allowed in brewing under the "Reinheitsgebot," a beer purity law established in Bavaria in 1516 by Duke Wilhelm IV. This law governed the production of lagers—bottom-fermented beers—by limiting the ingredients to maintain quality and purity. While this standard was observed in Greece for many years, recent updates to Greek regulations, aligned with European laws, now allow for the use of alternative starches and sugars, such as wheat malt, rice, corn, glucose syrup, maltose syrup and sugar, in beer production.

- **Barley (Malt):** As the core ingredient in beer, barley must undergo malting before it is used in the brewing process. The malted barley provides the sugars necessary for fermentation.
- **Hops:** Hops, the flowers of a climbing plant, are essential for adding both aroma and bitterness to beer. Their bitterness is derived from resins, while their essential oils contribute to the beer's distinctive fragrance. Hops also act as a natural preservative, extending the shelf life of the beer.
- **Water:** Water is the most abundant ingredient in beer, making up about 92–95% of its total volume. The mineral content of water from different regions in Greece plays a crucial role in shaping the flavor and quality of the beer.
- **Yeast:** Yeast, a living organism from the fungi family, is responsible for fermentation. It converts the sugars in the wort into alcohol and carbon dioxide, producing distinct flavors and aromas based on the yeast type and fermentation method. There are two main types of yeast: bottom-fermenting yeast, used for lager beers, and top-fermenting yeast, used for ales.

1.3 Market Dynamics and Export Trends

The craft beer market in Greece has experienced steady growth, with domestic production primarily serving the needs of the local market while also targeting both EU and non-EU export markets. In 2016, the total domestic production volume reached approximately 3.827 million hectoliters, reflecting an expanding industry trend. Exports have played a role in this growth, with breweries focusing on strengthening their presence in international markets. Greek breweries utilize strategic production practices to optimize output and meet demand efficiently, ensuring they align with the preferences of both domestic and international consumers (Ragkatsis, 2019).

1.4 Scope and Research Questions

This dissertation aims to examine the sales time series of eight beer products distributed by a craft brewery across the country. The objective is to identify key features and analyze the sales trends of these products. Additionally, the study seeks to draw conclusions about the sales patterns, assess the potential impact of the Covid-19 pandemic and determine the most effective models for generating accurate forecasts in a dynamic and uncertain market environment.

Utilizing a range of time series analysis and regression models over a four-year span from January 2020 to December 2023, the study conducts a detailed examination of the sales data. The goal is to provide the company with valuable insights and reliable predictions to support informed decision-making.

This research endeavors to address the following questions through an in-depth analysis of the sales data for the eight beer products in Greece:

1. What are the key patterns and statistical characteristics of the sales time series for the products? Which of these statistical attributes have the most significant impact on the sales trends over time? Are there particular products that exhibit more pronounced seasonal effects?
2. Is there evidence of interdependence in the sales patterns across various product types?
3. What is the usual level of accuracy achieved in forecasting monthly sales? Does this level of accuracy differ between various product categories?

4. What impact did the Covid-19 pandemic have on sales and the overall sales patterns of the products analyzed?

1.5 Research Outline

This dissertation is organized into six key chapters, each addressing the previously outlined research questions. The first chapter serves as an introductory framework, offering an overview of the craft beer industry in Greece and the scope of the study. It outlines the research objectives, questions and the structure of the dissertation.

The second chapter delivers a succinct literature review focused on forecasting methodologies within the spirits and alcoholic beverages industry. It highlights the critical role of forecasting in managing demand and emphasizes the importance of integrating Time Series and Regression Models into supply chain operations.

The third chapter elaborates on the research methodology used to build the theoretical framework for the empirical analysis presented in the fourth chapter. This section details the forecasting techniques, statistical methods and analytical tools employed to study the sales time series of the case company. The primary aim is to explore the sales trends and assess the forecasting accuracy of the models developed.

In the fourth chapter, the empirical analysis unfolds, offering an in-depth examination of the company's product sales data. This chapter investigates sales patterns and explores potential interdependencies among different beer products using core statistical techniques. It also assesses the impact of significant global disruptions, such as the Covid-19 pandemic, on sales trends. The chapter concludes by evaluating the forecasting models' accuracy through commonly used performance metrics.

The fifth chapter provides a summary of the key findings from the empirical analysis, focusing on addressing the research questions introduced in the first chapter. This section synthesizes the main insights and draws conclusions based on the data analyzed.

The final chapter, chapter six, brings together the conclusions and insights gained from the dissertation. It highlights the key learnings and suggests areas for future research in forecasting analysis, aiming to build upon and expand the current understanding in this field.

2. Literature Review

The spirits and alcoholic beverages industry, particularly the craft beer sector, is one of the most dynamic and rapidly evolving markets globally. Numerous multinational companies thrive in this arena, generating significant revenues while continually innovating their product lines, which include a variety of both alcoholic and non-alcoholic beverages.

Demand forecasting is a critical element in managing business processes within this industry. Despite the varying complexities and methodologies employed across different sectors, the primary goal remains the same: to produce accurate projections of future demand for products by analyzing historical sales data alongside current market and environmental factors (such as economic trends, regulatory changes and consumer preferences). Achieving precise forecasts poses an ongoing challenge, especially in the craft beer industry, where trends and consumer tastes can shift rapidly.

The complexities of the craft beer supply chain present significant challenges to achieving efficiency, sustainability, and accurate demand forecasting. While many studies emphasize consumer demand, the supply-side considerations crucial to operational success remain underexplored. Effective demand forecasting is foundational to strategic planning, yet many craft breweries rely on basic, spreadsheet-based tools, limiting their ability to predict and respond to market fluctuations accurately. Incorporating forecasting into a sustainable supply chain framework can enhance ingredient procurement, optimize recycling efforts, conserve energy, and streamline distribution systems. These practices not only reduce environmental impact but also align production more closely with demand, minimizing waste and improving operational efficiency (Bahl et al., 2021).

Furthermore, in their recent paper, Negrón Aching et al. (2024) emphasize the critical role of demand forecasting in enhancing productivity within the craft beer industry. Their research identifies the Winters method as a particularly effective tool for forecasting demand, achieving a mean absolute percentage error (MAPE) of 9.4%. By analyzing historical data and market trends, this model captures seasonal fluctuations and ensures a more accurate prediction of future demand. The study demonstrates how accurate demand forecasting serves as the foundation for aligning production schedules and optimizing inventory management. This approach reduces stockouts and overproduction, enabling craft beer producers to better respond to market dynamics and enhance overall operational efficiency.

As highlighted earlier, the supply chain for craft beer is intricate, involving multiple interconnected processes, which contribute to the various challenges faced by producers worldwide. Effective management of this complex chain is crucial, particularly in a sector where consumer expectations and regulatory landscapes can change swiftly. The Covid-19 pandemic exposed vulnerabilities within global logistics systems, revealing inefficiencies even among well-established players in the spirits and alcoholic beverages industry. This period underscored the importance of robust forecasting and supply chain management to navigate such disruptions successfully.

2.1 Prior Work

The initial literature review revealed that most prior research on sales forecasting for spirits and alcoholic beverages has focused on retail and distribution firms rather than the manufacturer's point of sale. For instance, Bratina and Faganel (2008) investigated beer consumption patterns for a leading brand in Slovenia, employing time series forecasting models to improve demand prediction accuracy. Recognizing significant seasonal effects, they utilized ARMA and ARMAX models to analyze daily sales data, integrating external variables such as temperature and promotional events. The model selection process emphasized diagnostic checks, including autocorrelation and cross-correlation functions, alongside statistical significance of coefficients. Unlike traditional methods relying on aggregated weekly or monthly data, their daily data approach demonstrated superior variance explanation. The study concluded that models with ARMA components, capturing autoregression and moving average factors, performed better than standard regression analyses. Additionally, while short-term promotional effects were detected, no evidence supported long-term impacts, aligning with prior research findings in the field.

The study by Fogarty and Voon (2018) delves into the long-term changes in alcohol consumption patterns across the United States, focusing on beer, wine and spirits. Using ARIMA models, the research forecasts per capita consumption trends, providing insights into how these trends evolve over time. The analysis also examines the convergence and divergence of consumption at the state level, revealing that while there was a general trend towards convergence from the 1970s to the early 2000s, this trend has recently reversed, leading to greater divergence among states. Additionally, the study explores the impact of state alcohol policies on consumption patterns. Interestingly, the findings suggest that there is no systematic relationship between these policy settings and the observed changes in alcohol consumption. This conclusion was reached through the use of Bayesian estimation

methods, which allowed for robust pairwise comparisons between states.

Additionally, Voon and Fogarty (2019) investigated methods for forecasting alcohol demand, focusing on U.S. per capita consumption data for spirits, wine and beer. Their study highlighted the importance of employing multiple forecasting approaches to capture the variability in consumption patterns across different beverages. The data was split into a training set (1970–2007) and a test set (2008–2012) and the models included single-equation ARIMA, state-space models, hierarchical ARIMA and state-space methods, BATS (Box-Cox transformation, ARMA errors, trend and seasonal components) and neural networks. Model selection was guided by the Akaike Information Criterion (AIC) and performance was evaluated using Root Mean Square Error (RMSE). The results showed no single method consistently outperformed the others across all beverage categories. BATS models were most effective for spirits, ARIMA excelled for wine and neural networks delivered the best forecasts for beer. Additionally, the study revealed that simpler models often performed as well as more complex ones, emphasizing the utility of combining forecasts to account for methodological uncertainties. The authors also showcased the capability of the R software platform to implement these methods, providing a practical toolkit for forecasting alcohol demand while illustrating the significance of considering multiple methods to enhance forecast accuracy and address the inherent uncertainties in long-range consumption predictions.

In their paper, Jiang et al. (2020) investigated demand forecasting for two vodka products distributed by a U.S.-based beverage company using time series and deep learning models. The dataset revealed strong customer-specific buying patterns and seasonality, leading to the creation of separate models for each product/customer combination. They utilized traditional ARIMA and ARUMA models, optimized using the Akaike Information Criterion (AIC), alongside advanced neural architectures like CNN-LSTM and biLSTM. Model performance was validated using rolling-window cross-validation with Mean Absolute Error (MAE) as the metric. Results showed time series models excelled for stable data, while deep learning outperformed for high-variance patterns. Notably, CNN-LSTM reduced error by up to 49%, but naive models remained competitive for highly seasonal data, emphasizing the need for tailored approaches in demand forecasting.

In a recent study conducted by Ford et al. (2020) introduced an automated machine learning (AutoML) framework aimed at improving inventory management and purchasing decisions for a U.S.-based beverage alcohol distribution company. The framework focused on

identifying the most accurate forecasting model for predicting standard case sales. It incorporated a variety of classical time series models, such as ARIMA, equal means and ARMA variants, alongside advanced approaches like multilayer perceptrons (MLPs) and random forests (RFs). The development process began with analyzing the stationarity and irregular components of the sales time series data. Stationarity was assessed using the Augmented Dickey-Fuller (ADF) and Kwiatkowski-Phillips-Schmidt-Shin (KPSS) tests. Additionally, the Ljung-Box Q (LBQ) statistic, along with autocorrelation (ACF) and partial autocorrelation (PACF) functions, was applied to evaluate whether the series exhibited white noise characteristics. Model performance was evaluated using the Bayesian Information Criterion (BIC) and further validated with a rolling window mean squared error (MSE) to track accuracy over time. To determine whether autoregressive (AR) models outperformed the equal means model, the researchers conducted an analysis of variance (ANOVA), providing statistical clarity on model performance differences.

This research aims to contribute to the sales forecasting literature by developing an accurate and practical forecasting tool tailored to optimize the value chain for the case company. The study seeks to uncover sales trends, identify interdependencies among product categories and support informed decision-making within sales and supply chain operations, especially in today's volatile environment.

3. Research Methodology

This chapter focuses on examining the methodology used to address the research questions presented in the opening chapter of this dissertation. Its aim is to provide a thorough explanation of the study's approach, detailing how it was applied within the context of craft beer sales in Greece. The research relies heavily on quantitative statistical methods, analytical techniques and forecasting tools to derive insights from sales data related to eight different style beers distributed by the company in the Greek market.

The study begins by gathering and analyzing monthly sales data for these eight products over a four-year timeframe, spanning from January 2020 to December 2023. Using Excel's descriptive statistics feature, the initial analysis explores the fundamental statistical characteristics of each product's sales data. This is followed by a visual analysis through graphical summaries and boxplots, aiming to identify outliers, trends and cycles. The purpose of this step is to uncover key patterns and characteristics within the data, laying the groundwork for more detailed analysis.

Furthermore, the use of Multiple Linear Regression (MLR) models for each product seeks to analyze their statistical properties, identify seasonal patterns, detect potential autocorrelation issues, explore interdependencies among the sales data and evaluate the impact of the Covid-19 pandemic on these factors. Each aspect of this analysis is addressed through the application of a corresponding MLR model. Based on the results, adjustments will be made by adding new variables or removing those deemed unnecessary to refine the model. Only variables demonstrating statistical significance at the 5% level will be retained in the final version of the model.

Subsequently, two distinct forecasting models will be developed, with their performance evaluated and compared using metrics like Mean Absolute Error (MAE) and Mean Absolute Percentage Error (MAPE). A reliable quantitative forecasting method is invaluable across various industries, enhancing operational efficiency, supporting strategic decision-making and securing a competitive edge, as highlighted in the introductory chapter. The goal of estimating these forecasting models is to identify the most suitable tool for predicting each product's sales, thereby enabling data-driven decisions and improving business outcomes.

3.1 Regression Analysis

Regression analysis is one of the most widely used quantitative methods in market research, primarily focused on examining the relationship between dependent and independent

variables. In marketing applications, the dependent variable often represents a key metric, such as sales, while independent variables include factors believed to influence it. Through the application of regression analysis, valuable insights can be obtained about whether the dependent variable is significantly influenced by the independent variables and the degree to which changes in the dependent variable can be explained by them. Additionally, it provides estimates regarding the strength and direction of these relationships.

This technique also facilitates forecasting by offering predictive insights and evaluating the accuracy of those predictions. Both simple linear regression (SLR) and multiple linear regression (MLR) models are typically expressed using the following general equation:

- For Simple Linear Regression: $Y = \beta_0 + \beta_1 X_1 + e$ (3.1.1)
- For Multiple Linear Regression: $Y = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \dots + \beta_k X_k + e$ (3.1.2)

where β_0 represents the intercept, often referred to as the constant term, which indicates the average value of the dependent variable when all independent variables are set to zero, β_i denotes the coefficients that correspond to the explanatory variables X_i and reflect the impact of each predictor on the dependent variable Y . Furthermore, the term e signifies the disturbance or error component, accounting for the portion of variability in the dependent variable that the model does not explain or predict.

3.1.1 Model Building Framework

According to Mentzer Jr. and Moon (2004), the process of using regression analysis for sales forecasting consists of three key stages, as outlined in **Figure 2**. The initial stage focuses on selecting a suitable set of explanatory variables. This phase is primarily qualitative, relying heavily on the analyst's expertise and understanding of factors that may influence demand. The second stage involves constructing an initial model, which undergoes statistical evaluation to determine its suitability for forecasting future sales. Key evaluation criteria include the R-squared value, which reflects how much of the variation in the dependent variable (e.g., demand) is explained by the predictors, the C_p statistic (Mallows' C) for assessing model bias and stability and the statistical significance of the regression coefficients b_i , typically tested through methods like t-tests or Wald statistics. Additionally, adherence to the assumptions of the Ordinary Least Squares (OLS) method—such as model fit and absence of autocorrelation—will be thoroughly examined later in the study.

The final stage involves assessing the model's performance, ensuring its ability to make accurate predictions across different datasets and time periods. This validation step is essential for determining the model's robustness in forecasting future values of the dependent variable.

In this research, the process of developing an appropriate regression model closely follows the framework suggested by Mentzer Jr. and Moon (2004). Initially, relevant variables will be identified for inclusion in the model. Next, a preliminary model will be established and subjected to the necessary statistical tests outlined in the methodology section. Lastly, the model's validity will be evaluated. Should the initial model fail to deliver consistent and unbiased predictions, additional explanatory variables will be incorporated and the regression analysis will be repeated to improve its accuracy.

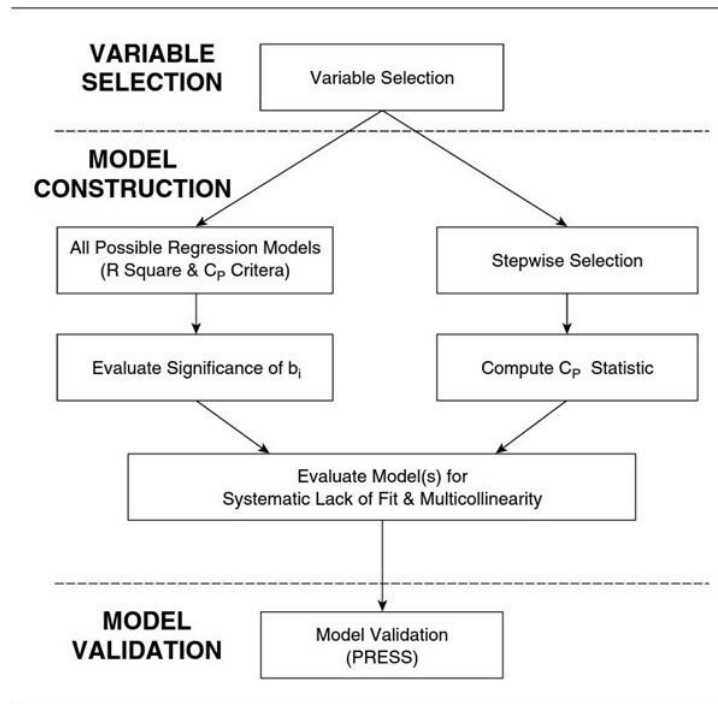


Figure 2, “The Regression analysis process”. Source: Mentzer and Moon, (2004)

In econometric analyses, researchers often use simple and multiple regression techniques to forecast future values of population parameters based on available sample data. The mathematical representation of the sample regression model is expressed as:

$$\hat{Y} = \hat{\beta}_0 + \sum_{i=1}^N \hat{\beta}_i X_i \quad (3.1.1.1)$$

where β_0 and β_i represent the estimations of the population parameters.

In linear regression analysis, the Ordinary Least Squares (OLS) method is the most commonly utilized technique for estimating population parameters. It plays a crucial role in

statistical modeling by fitting a linear equation to the data, aiming to minimize the total squared deviations between the actual values and the predicted outcomes.

3.1.2 Ordinary Least Squares

As noted by Hutcheson and Sofroniou (1999), the OLS technique is widely recognized and frequently used for forecasting population parameters through simple or multiple linear regression models. By utilizing OLS, a regression line is generated that closely fits the data points, offering a precise representation of their distribution. The essence of the least squares principle lies in constructing a line that minimizes the total squared differences between the actual data points and the values predicted by the regression line, ensuring the smallest possible deviations.

The primary goal of OLS regression is to reduce the Sum of Squared Residuals (SSR) within the sample regression framework. SSR, also referred to as the “Sum of Squared Errors”, represents the aggregated squared differences between the observed values and those estimated by the regression model. It provides a measure of the overall error in the model by capturing the total squared variances between actual outcomes and predicted results. Mathematically, SSR is determined by taking the differences between the observed dependent variable values and the regression equation’s predicted values, squaring these differences, and summing them up across all data points. This value reflects the degree of misfit between the observed data and the model’s predictions, with the following formula used to calculate SSR:

$$SSR = \sum_{t=1}^T \hat{e}_t^2 = \sum_{t=1}^T (Y_t - \hat{Y}_t)^2 \quad (3.1.2.1)$$

where T is the sample size.

The OLS regression technique is grounded in several key assumptions that must be validated before proceeding with the analysis. These essential assumptions are summarized below:

- **Linearity in relationships.** This assumption requires that a linear connection exists between the independent variables and the dependent variable, ensuring that the model accurately captures the relationships within the data.
- **Independence of residuals (non-autocorrelation).** This principle stipulates that the residuals in the regression model should not display any systematic correlation, indicating that errors across observations are independent of each other.

- Normal distribution of residuals. The errors or residuals in the regression model are expected to follow a normal distribution, centering around the regression line.
- Homogeneity of variance (homoscedasticity). This assumption ensures that the variability of the dependent variable around the regression line remains constant across all values of the independent variables.
- No perfect multicollinearity. Perfect multicollinearity arises when one or more independent variables are exactly predictable from a combination of other variables. Such a situation complicates regression analysis, making it impossible to determine unique coefficients for the independent variables.

This study plans to apply multiple linear regression extensively throughout the empirical analysis. The research objectives include assessing statistical properties of time series data, identifying interconnections among product categories, evaluating the effects of Covid-19 on sales patterns and constructing a predictive model for future sales.

3.2 Exponentially Weighted Moving Average

In addition to using regression analysis to identify characteristics of sales time series and predict future demand, the Exponential Weighted Moving Average (EWMA) model is another widely applied approach in time series forecasting. The EWMA model assigns different weights to observations collected sequentially over time, with more recent data points receiving greater emphasis. This weighting approach allows the model to better reflect evolving patterns in the data. As highlighted by Luxenberg and Boyd (2024), the EWMA model features a beneficial recursive structure, which improves its computational efficiency. Moreover, it does not rely on assumptions about data distribution or require prior knowledge of the time series, making it highly versatile.

The EWMA model is particularly effective in capturing short-term variations and temporal fluctuations within a time series by incorporating prior observations and predictions into its forecasts. However, its performance may be limited in situations where the time series is influenced by multiple variables. The model uses a smoothing parameter, λ , which ranges from 0 to 1, to determine the weight given to past observations. A higher value of λ places more emphasis on historical data, while a lower λ prioritizes recent observations for forecasting (Thomaidis, 2021). The following equation represents the EWMA model and mathematically formalizes this approach:

$$\hat{Y}_{t+1} = \hat{Y}_{t+1}(\lambda) = (1 - \lambda)Y_t + \lambda\hat{Y}_t \quad (3.2.1)$$

where \hat{Y}_{t+1} represents the predicted value for the upcoming period $t + 1$, Y_t signifies the actual observed value for the current period t while \hat{Y}_t is the estimate for the same period and parameter λ , often called the smoothing factor or weight, determines the influence of past observations on the forecast.

The λ parameter ranges between 0 and 1 ($0 < \lambda < 1$) and plays a critical role in the effectiveness of the EWMA model. Choosing an appropriate λ value is essential, as it directly affects how the model integrates relevant data and aligns with the forecasting goals established by the analyst.

3.3 Forecast Accuracy Measures

Over time, various criteria have been utilized to assess the performance of forecasting techniques. These include analyzing forecasting errors, evaluating computational efficiency and examining the ability of the method to provide clear and interpretable results. Botchkarev (2019) highlights the critical importance of accuracy measures in addressing real-world challenges. When managing multiple variables, commonly accepted forecast error metrics are often applied to evaluate forecasting methods and identify the most suitable approach. Although these metrics have certain limitations, a consistent set of standard error measurements is widely used across different fields for this purpose.

The forecast error, \hat{e}_t , is defined as the difference between the actual observed value, Y_t , in period t , and the forecasted value, \hat{Y}_t , for the same period. Mathematically represented in equation (3.3.1), the forecast error reflects the unpredictable component of demand. This measure is crucial for a company's supply chain and planning activities, as significant inaccuracies in demand predictions can necessitate the development of contingency strategies to improve decision-making efficiency (Chopra & Meindl, 2013).

$$\hat{e}_t = Y_t - \hat{Y}_t \quad (3.3.1)$$

No matter how sophisticated the forecasting methods are, the predicted demand will almost always deviate from the actual demand, being either higher or lower but rarely exactly equal. Negative forecast error values signify that demand has been overestimated, whereas positive values indicate an underestimation. Key metrics used to evaluate forecasting errors are outlined as follows:

- Mean Absolute Error (MAE) or Mean Absolute Deviation (MAD)

- Mean Absolute Percentage Error (MAPE)
- Mean Squared Error (MSE)
- Root Mean Squared Error (RMSE)

3.3.1 Mean Absolute Error

The Mean Absolute Error (MAE) is a commonly used statistic for assessing the accuracy of predictions. It quantifies the average size of errors between the actual and forecasted values, without considering whether the errors are positive or negative. To compute the MAE, one takes the mean of the absolute differences between observed and predicted values for all data points. This metric provides a clear indication of the average error magnitude, with smaller MAE values signifying higher accuracy. MAE is widely applied in disciplines such as economics, finance, and machine learning to evaluate the effectiveness of predictive models or forecasting techniques. Its mathematical expression is given by the following formula:

$$MAE = \left(\frac{1}{T}\right) \sum_{t=1}^T |Y_t - \hat{Y}_t| = \left(\frac{1}{T}\right) \sum_{t=1}^T |\hat{e}_t| \quad (3.3.1.1)$$

where $|\hat{e}_t|$ is the absolute value of the error in period t and T is the sample size.

3.3.2 Mean Absolute Percentage Error

The Mean Absolute Percentage Error (MAPE) is a commonly employed measure for evaluating the accuracy of forecasting models, much like the previously mentioned MAE. It calculates the average absolute deviation between actual and predicted values, expressed as a percentage. To determine MAPE, the absolute differences between predicted and observed values for each time period are computed, divided by the actual values and then averaged over all data points. This metric focuses on the magnitude of errors without regard to their direction, emphasizing the scale of deviations.

As with the MAE, lower MAPE values correspond to higher forecasting accuracy. However, it is important to recognize MAPE's limitations, particularly when dealing with values close to zero. In such cases, percentage errors can become disproportionately large, potentially distorting the overall accuracy evaluation. Despite these challenges, MAPE is widely used across various fields, including economics, supply chain management and finance, to assess the performance of forecasting models and compare the precision of different methodologies. The MAPE formula is mathematically represented as follows:

$$MAPE = \left(\frac{1}{T}\right) \sum_{t=1}^T \frac{|Y_t - \hat{Y}_t|}{Y_t} = \left(\frac{1}{T}\right) \sum_{t=1}^T \frac{|\hat{e}_t|}{Y_t} \times 100\% \quad (3.3.2.1)$$

where $|\hat{e}_t|$ is the absolute value of the error in period t , Y_t is the actual value for the same period and T is the sample size.

4. Empirical Study

This chapter focuses on the analysis of sales time series for the eight products examined in this case study. It will highlight the statistical properties of each product while exploring the insights gained from both the regression analysis and EWMA models. The accuracy and performance of the forecasting methods will also be evaluated using the metrics discussed in the previous chapter. Additionally, the chapter will investigate potential relationships between the time series and examine the possible effects of the Covid-19 pandemic on sales trends. The overarching goal is to conduct a comprehensive analysis of the sales data and address the research questions outlined in the thesis.

4.1 Time Series Data Selection

The data in this analysis was obtained from a craft beer brewery through the company's enterprise resource planning (ERP) software. This dataset consists of the monthly sales volume for eight different beer styles (Ale, IPA, Lager, Pilsner, Porter, Sour, Stout and Wheat Beer) over a four-year period, spanning from January 2020 to December 2023. Each product's dataset comprises 48 observations, without any missing records that might potentially disrupt the analytical process.

4.2 Descriptive Statistics

In this section of the analysis, our aim is to analyze the time series of product sales, utilizing Excel's Descriptive Statistics Tool, and extract significant insights about the main characteristics of the sales data. According to Newbold et al. (2020), descriptive statistics encompass both numerical techniques and graphical methods used to organize and explain the characteristics or variables within a given sample. The authors emphasized that the primary aim of descriptive statistics is to highlight the central value within a data distribution—commonly referred to as the mean or central tendency—and to describe the level of variability among the remaining data points. This variability, often termed dispersion or variance, reflects the extent to which values differ from the central point in the dataset.

Tables 1 and **2** highlight the primary attributes related to product sales for each of them within the examined period spanning from 2020 to 2023. These tables provide a comprehensive overview of key characteristics related to the sales data within the designated timeframe. They present the central tendency of sales, the spread of the data as indicated by the standard deviation and offer further understanding of the dataset's distribution by

analyzing skewness and kurtosis metrics.

Statistics	Ale	IPA	Lager	Pilsner
Mean	5,343,778.96	5,541,860.42	5,499,189.38	5,393,682.50
Standard Error	124,530.83	146,495.05	114,546.10	125,658.03
Median	5,472,450	5,573,175	5,495,770	5,234,980
Standard Deviation	862,774.92	1,014,947.47	793,598.66	870,584.35
Sample Variance	744,380,564,677.62	10,301,183,74,204.08	629,798,825,508.11	757,917,110,474.47
Kurtosis	-0.12	-0.14	0.40	-0.27
Skewness	-0.07	0.16	-0.04	0.54
Range	3,876,750	4,736,360	3,867,780	3,832,840
Minimum	3,634,390	3,409,090	3,403,460	3,958,930
Maximum	7,511,140	8,145,450	7,271,240	7,791,770
Sum	256,501,390	266,009,300	263,961,090	258,896,760
Count	48	48	48	48

Table 1 “Descriptive Statistics of products Ale, IPA, Lager and Pilsner”

An analysis of each beer category reveals that **IPA** stands out with the highest average demand, making it a key player in the portfolio. However, this strong position comes with considerable variability, as indicated by its high standard deviation, suggesting that demand for **IPA** is more volatile and more prone to fluctuations compared to the other categories. Additionally, **IPA** has a slight positive skew, hinting at occasional surges in demand, while its low kurtosis value implies a distribution with lighter tails, meaning fewer extreme values.

Statistics	Porter	Sour	Stout	Wheat Beer
Mean	5,341,806.04	5,352,150.42	5,600,112.71	5,553,390.00
Standard Error	114,545.49	131,228.39	133,971.37	134,097.65
Median	5,323,905	5,312,565	5,511,425	5,454,885
Standard Deviation	793,594.44	909,176.93	928,180.89	929,055.79
Sample Variance	629,792,141,003.15	826,602,698,484.93	861,519,759,990.38	863,144,666,208.51
Kurtosis	-0.57	0.19	0.01	0.92
Skewness	0.31	0.48	-0.08	0.46
Range	3,259,330	4,008,360	4,422,960	4,764,300
Minimum	4,011,860	3,469,840	3,133,360	3,785,700
Maximum	7,271,190	7,478,200	7,556,320	8,550,000
Sum	256,406,690	256,903,220	268,805,410	266,562,720
Count	48	48	48	48

Table 2 “Descriptive Statistics of products Porter, Sour, Stout and Wheat Beer”

Stout also displays a high average demand level similar to **IPA** and shows considerable volatility, reflected in its high standard deviation. **Stout**’s positive skewness suggests occasional demand spikes, aligning with a pattern of demand that is not fully stable. The

kurtosis value is close to zero, indicating a flatter distribution, which suggests fewer extreme outliers but still noticeable variability. This pattern is somewhat mirrored by **Wheat Beer**, which also shows a high demand with moderate stability, as indicated by its slightly lower standard deviation. **Wheat Beer**'s positive skewness and higher kurtosis suggest that while generally stable, it does experience occasional demand peaks, contributing to a more peaked distribution.

Ale and **Pilsner** exhibit moderate demand levels, but their standard deviations indicate substantial fluctuations in their respective demand patterns. **Pilsner**, in particular, shows a noticeable rightward skew, suggesting a likelihood of higher-demand outliers. Its negative kurtosis points to a somewhat flat distribution with less clustering around the mean. In contrast, **Ale**'s demand is close to being symmetrical, as shown by its near-zero skewness, although it still shows considerable fluctuations.

The **Lager** category, however, stands out for its stability. With the lowest standard deviation among the four categories, **Lager**'s demand is the most consistent. Its near-zero skewness and kurtosis values indicate a nearly normal distribution, suggesting that **Lager** experiences fewer extreme highs or lows in demand. The close alignment of its mean and median values further supports its steady demand profile.

Porter has lower demand volatility, as indicated by a lower standard deviation and kurtosis near zero, pointing to a stable demand profile with fewer extreme values. Its skewness is close to zero, showing a fairly symmetrical distribution. Similarly, **Sour** has a moderate demand level and a slight positive skew, with a degree of variability that is slightly higher than **Porter**'s but still within a stable range.

Tables 3, 4 and 5 present a clear summary of two key statistical metrics—mean and sample variance—for each product over the years. This compilation is designed to support the upcoming analysis by providing vital information about these important statistical measures for each product in the dataset.

Years	Ale		IPA		Lager	
	Mean	Variance	Mean	Variance	Mean	Variance
2020	5,565,235.83	174,489,570,481.06	5,343,831.67	835,184,497,560.61	5,501,830.83	461,455,960,881.06
2021	5,306,851.67	1,159,970,397,106.06	5,988,730.83	1,376,120,960,208.34	5,540,200.00	943,064,005,800.00
2022	5,221,324.17	1,221,840,030,481.06	5,320,411.67	923,787,097,869.70	5,518,291.67	598,684,042,851.52
2023	5,281,704.17	548,683,983,971.97	5,514,467.50	951,378,524,093.18	5,436,435.00	681,218,036,409.09

Table 3 “Mean and sample variance of Ale, IPA and Lager beers during the years”

	Pilsner		Porter		Sour	
Years	Mean	Variance	Mean	Variance	Mean	Variance
2020	5,272,783.33	845,616,209,387.88	5,109,779.17	358,946,132,371.97	5,135,700.00	302,072,768,090.91
2021	5,286,468.33	949,408,457,615.15	5,414,059.17	803,968,506,117.43	5,459,742.50	1,160,126,962,038.64
2022	5,509,716.67	675,872,710,824.24	5,795,223.33	706,812,251,206.06	5,143,374.17	879,827,957,462.88
2023	5,505,791.67	710,598,835,869.70	5,048,162.50	438,435,071,238.64	5,669,785.00	968,468,107,354.55

Table 4 “Mean and sample variance of Pilsner, Porter and Sour beers during the years”

	Stout		Wheat Beer	
Years	Mean	Variance	Mean	Variance
2020	5,585,355.83	687,082,595,408.34	5,693,272.50	1,470,873,606,329.55
2021	5,102,987.50	796,040,358,456.82	5,256,218.33	801,420,339,560.61
2022	5,999,943.33	1,165,457,676,787.88	5,786,350.83	389,703,446,135.61
2023	5,712,164.17	574,526,020,808.34	5,477,718.33	842,847,929,833.34

Table 5 “Mean and sample variance of Stout and Wheat Beer during the years”

4.2.1 Graphical Summary per Product

In time series analysis, a key goal is to investigate and understand the variations within the data being studied. This exploration provides valuable insights, enabling researchers to assess how variables change over time and evaluate their potential for accurate forecasting. As noted by Lye and Hirschberg (2020), visual representations of these variables allow analysts to identify critical issues related to the presence of systematic or random fluctuations and patterns, offering a deeper understanding of the temporal behavior throughout the examined period.

Graphical visualization plays a vital role in time series analysis, serving as a powerful tool for identifying key recurring components in the data. These components typically include the overall trend, seasonal patterns and the random or irregular fluctuations often referred to as noise. By visually examining the data, the unique characteristics of these components become evident, enhancing the analytical process and enabling a more thorough interpretation of the time series structure. In the sections that follow, each product will be analyzed using time series graphs, histograms and boxplots to provide a detailed assessment. These visual tools will offer a clear view of the data’s patterns and distribution, facilitating a more in-depth evaluation and understanding of the underlying dynamics.

Product Ale

Figures 3, 4 and 5 display the time series plot, histogram and boxplot, providing a visual depiction of the data distribution, temporal trends and variability within the analyzed dataset. These graphical representations are valuable tools for understanding the underlying dynamics and characteristics of the data being examined.

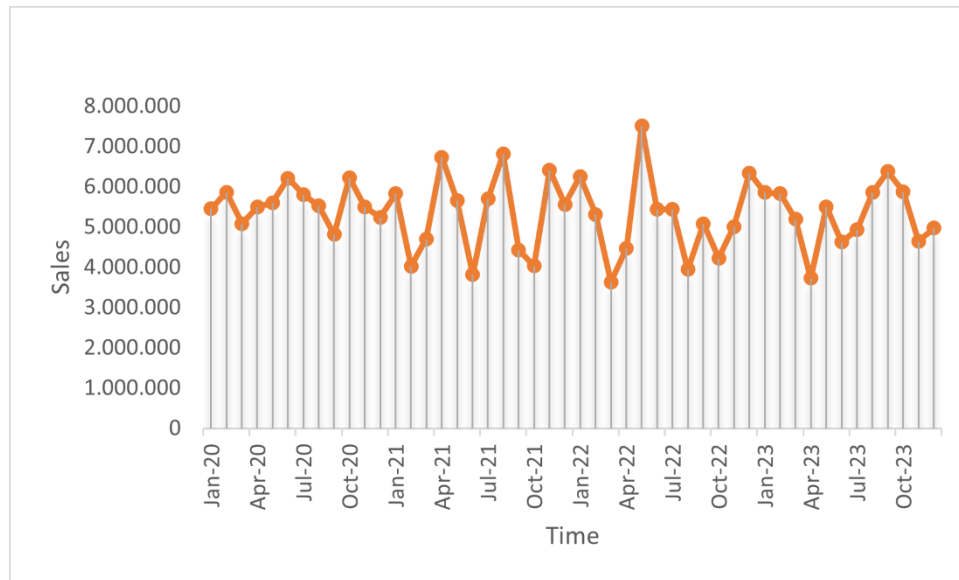


Figure 3, “Time series plot of Ale sales 2020-2023”

The time series plot charts the sales trends from January 2020 to December 2023, capturing the fluctuations over time. **Ale** sales exhibit a cyclical or seasonal pattern, with regular peaks and troughs suggesting recurring high and low periods, possibly due to seasonal demand or events. For example, there are notable spikes in early 2022 and mid-2023, which might reflect specific factors driving higher sales during those times. Despite these periodic fluctuations, the plot shows no clear long-term upward or downward trend, implying that overall sales levels have remained fairly stable over this period. However, the short-term variations indicate that while sales are consistent on an annual basis, they do fluctuate significantly from month to month.

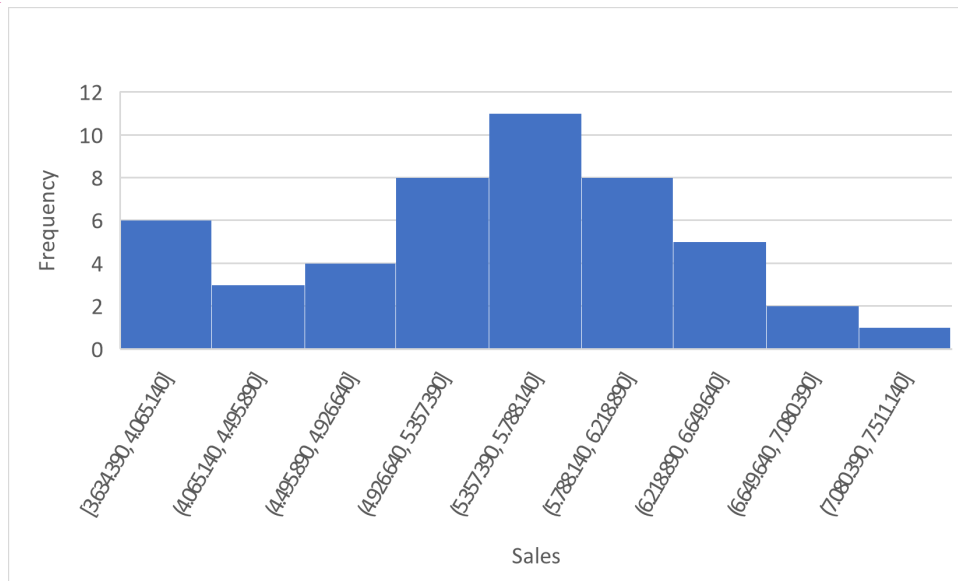


Figure 4, “Histogram of Ale sales”

The histogram reveals a roughly normal distribution shape, with fewer occurrences of very low or very high sales, suggesting that extreme monthly sales figures are rare. This distribution implies stability, as the majority of sales values fall within a predictable range. The shape also provides insight into the central tendency and dispersion of monthly sales, reinforcing that **Ale**’s sales rarely deviate far from the average.

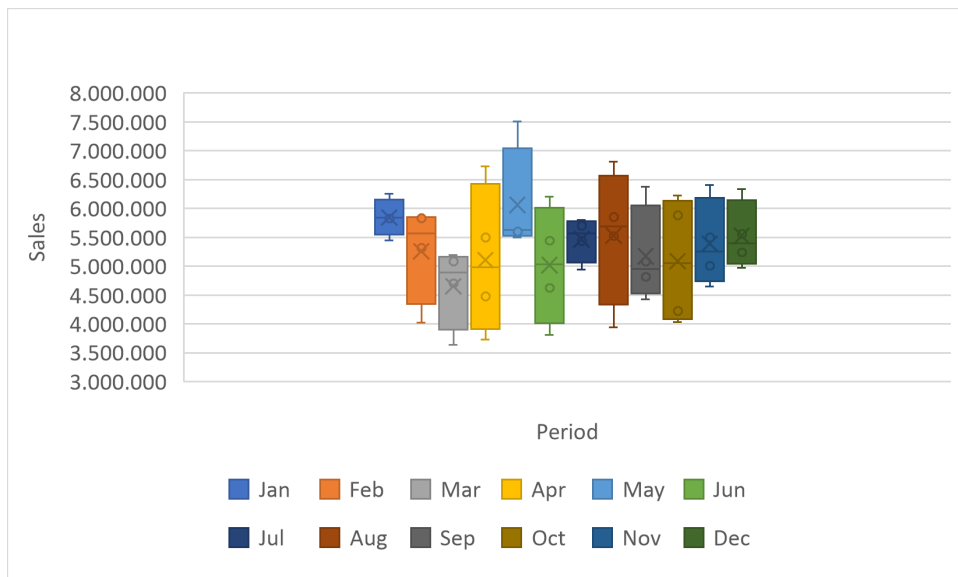


Figure 5, “Monthly Boxplot of Ale sales”

The box plot provides a visual representation of **Ale**’s monthly sales distribution across a year. The graph reveals that while **Ale** experiences some seasonal and monthly variability, most months fall within a relatively stable range. Certain months are more consistent, which allows for predictable planning. However, outliers are also visible which indicate unusually high or low sales values. These outliers suggest that certain months experience either

unexpected sales spikes or dips, potentially due to seasonal effects or specific events impacting sales.

Product IPA

The graphical summary continues with **IPA** in **Figures 6-8**, using the same approach and methodology applied to the previous product.

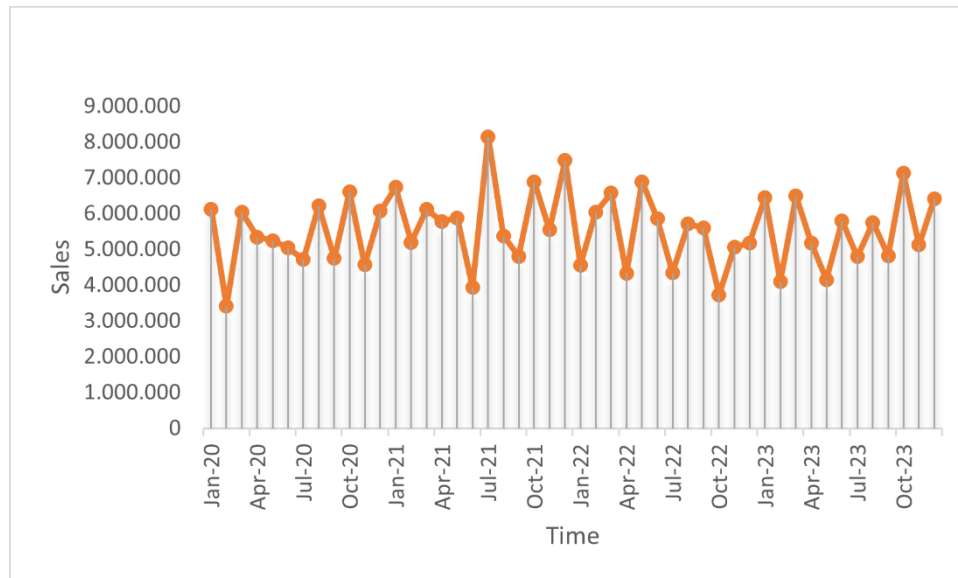


Figure 6, “Time series plot of IPA sales 2020-2023”

The time series plot, which spans the examined period, provides a more detailed look at sales trends over time. It shows regular fluctuations, suggesting possible seasonality, with recurring peaks and dips at certain times of the year. However, there is no clear upward or downward trend, which implies that **IPA** sales remain steady over the observed period. Although there are fluctuations, they tend to hover around the average sales value, supporting the notion of stability in demand. This seasonal pattern, while present, is not overly pronounced, indicating that sales peaks are relatively moderate and predictable.

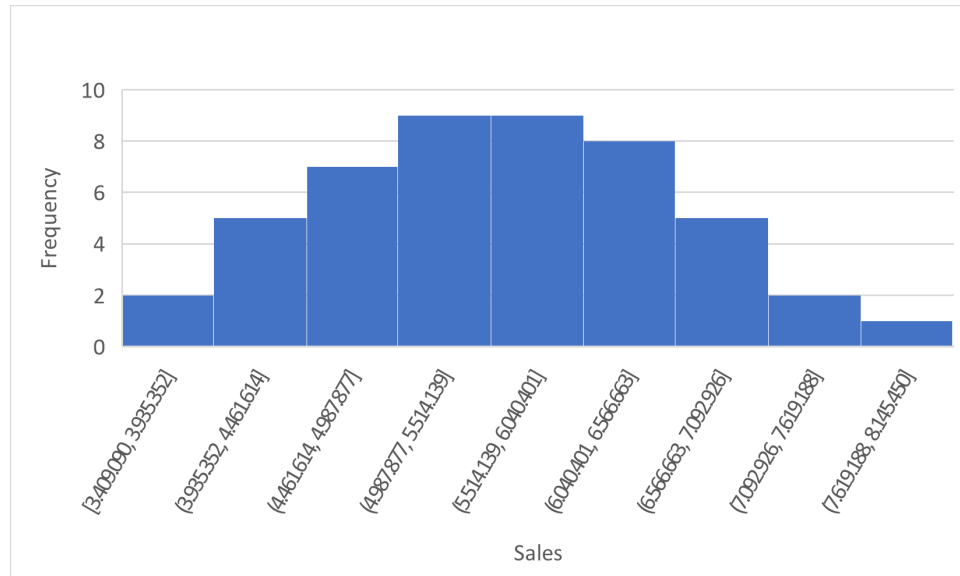


Figure 7, “Histogram of IPA sales”

The analysis of **IPA** sales data reveals a generally consistent trend with some moderate month-to-month variation. The histogram of sales distribution suggests that the monthly sales figures are centered around a common range. Although the distribution is somewhat symmetric, it has a slight right skew, reflected in the skewness value of 0.16. This rightward skew suggests a few instances of exceptionally high sales, but there are no significant outliers on the lower end of the distribution.

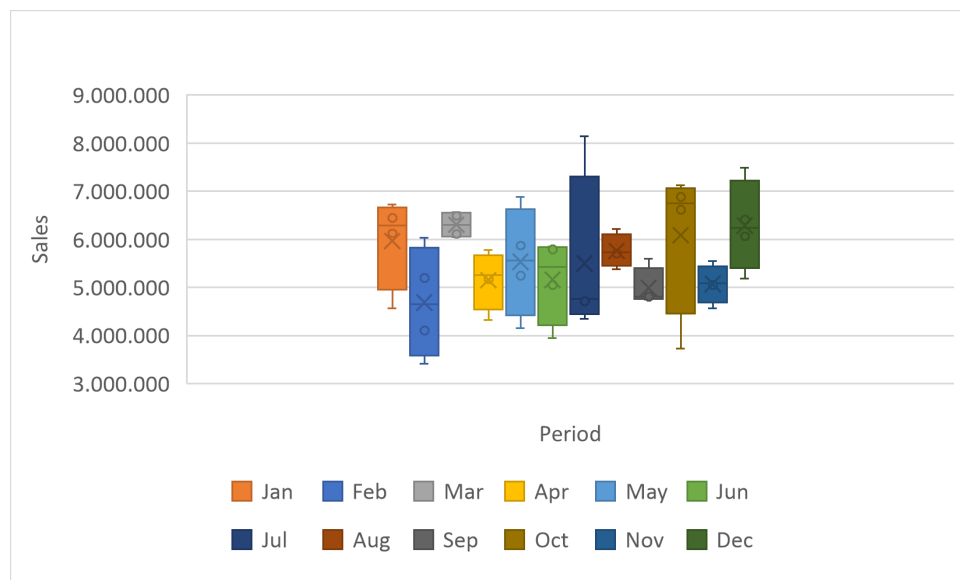


Figure 8, “Monthly Boxplot of IPA sales”

The monthly box plot highlights the variation in **IPA** sales across different times of the year. Some months, such as October and July, show larger and wider box plots, signifying greater variability in sales. October, in particular, has the widest range, indicating that sales in this month can fluctuate significantly. In contrast, months like February, May and December

display narrower boxes, suggesting more stable and consistent sales levels. The median sales values for most months fall close to or slightly above the overall mean, reinforcing the idea of a steady sales pattern without extreme highs or lows.

Product Lager

Figures 9-11 present the graphical summary for **Lager**, employing the same approach and methodology as used for the prior product.

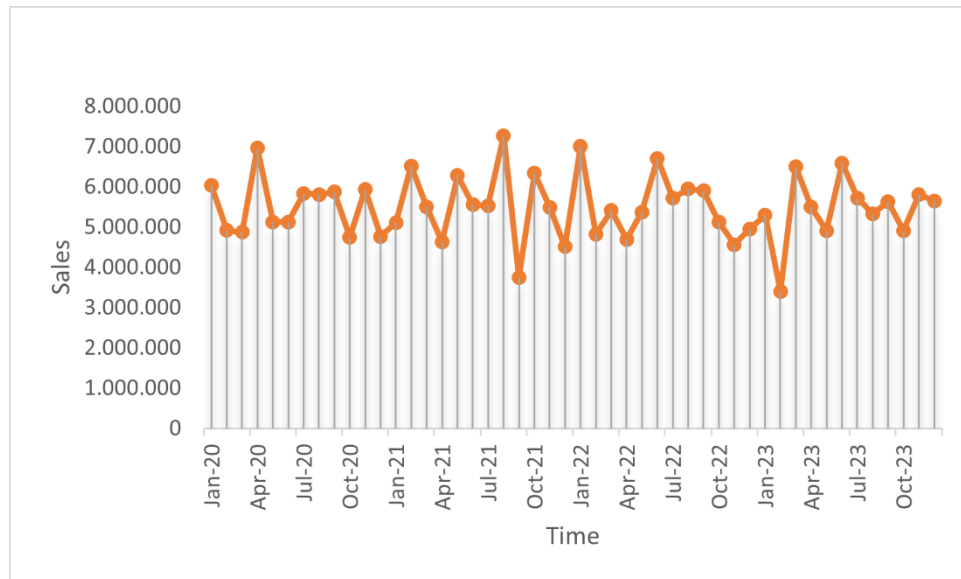


Figure 9, “Time series plot of Lager sales 2020-2023”

The time series plot illustrates the trend of **Lager** sales over a four-year period, showing clear patterns of seasonality. There are regular peaks in sales observed around the middle of each year, likely coinciding with increased demand during summer months or specific promotional periods. Conversely, dips in sales are often seen toward the end of the year. Despite these seasonal variations, the overall trend appears stable, without any noticeable long-term upward or downward shifts. The relatively low standard deviation reinforces this stability, indicating that while there are fluctuations due to seasonality, they do not significantly deviate from the overall average sales.

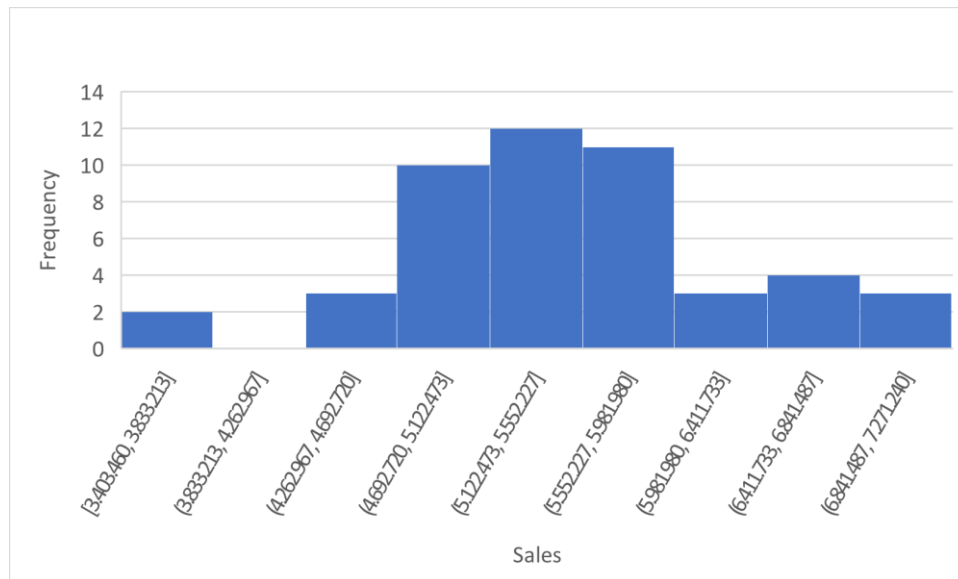


Figure 10, “Histogram of Lager sales”

The histogram of **Lager** sales reveals a distribution that closely resembles a normal curve, with the highest frequency of sales occurring in the range of 5,122,473 to 5,981,980. This aligns well with both the mean (5,499,189) and median (5,495,770), confirming that most of the sales data points are clustered around the central values. There are fewer data points at the lower and upper ends, indicating that extreme sales values are relatively uncommon. The symmetrical appearance of the histogram, combined with the low skewness, supports the notion of a normal-like distribution. This suggests that the **Lager** sales exhibit a regular pattern without significant deviations, aiding in consistent sales forecasting.

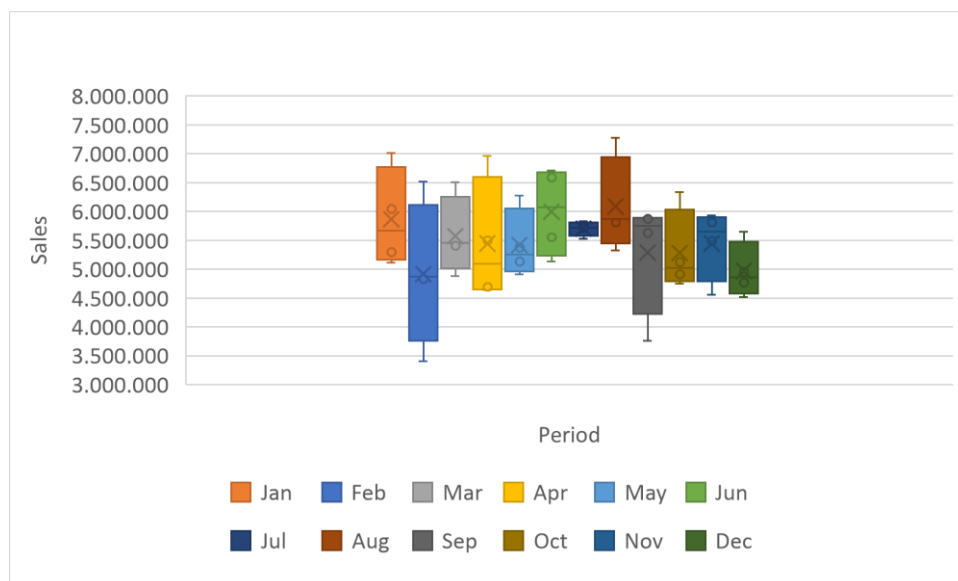


Figure 11, “Monthly Boxplot of Lager sales”

The box plot for **Lager** sales across different periods shows a well-centered distribution. The low skewness value of -0.04 implies that the data is almost symmetrical, meaning there are

no significant biases toward either high or low sales figures. The kurtosis value of 0.40 suggests the sales data distribution does not have extreme tails, further supporting the idea of balanced performance. Overall, the Lager sales data appear stable, with minimal unusual fluctuations, indicating a product with predictable market behavior.

Product **Pilsner**

The graphical summary for **Pilsner** is displayed in **Figures 12-14**, following the same approach and methodology applied to the previous product.

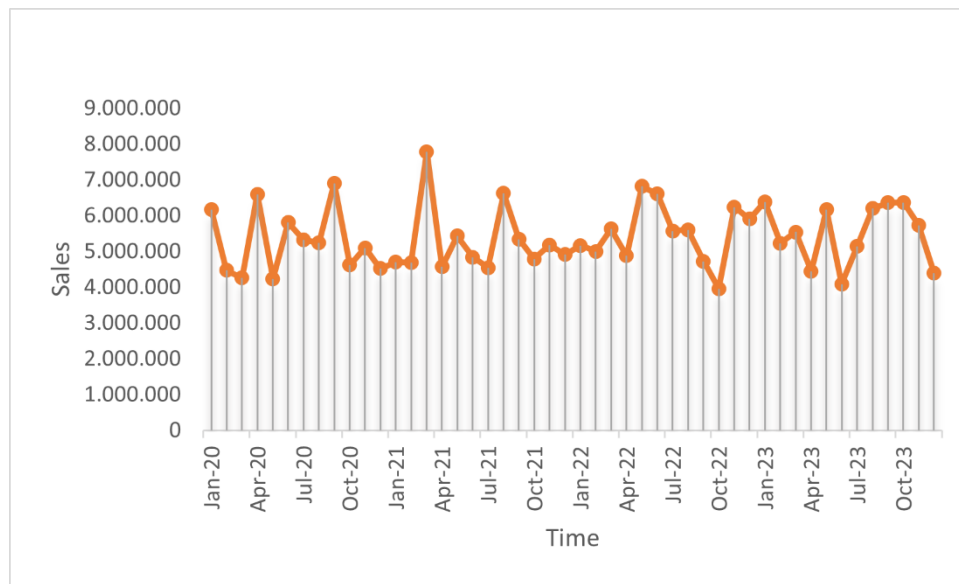


Figure 12, “Time series plot of Pilsner sales 2020-2023”

The time series plot shows periodic peaks and troughs, suggesting that **Pilsner** sales may experience seasonality, with certain months showing higher sales consistently across years. The line chart connecting each month’s data points captures these fluctuations and indicates some repeating cycles, though the sales trend overall appears stable without a marked upward or downward movement. Occasional sharp increases and decreases are noticeable, hinting at potential external factors or specific events influencing sales in those months. However, despite these fluctuations, **Pilsner** sales do not show significant long-term growth or decline, which could indicate a steady demand base with seasonal influences.

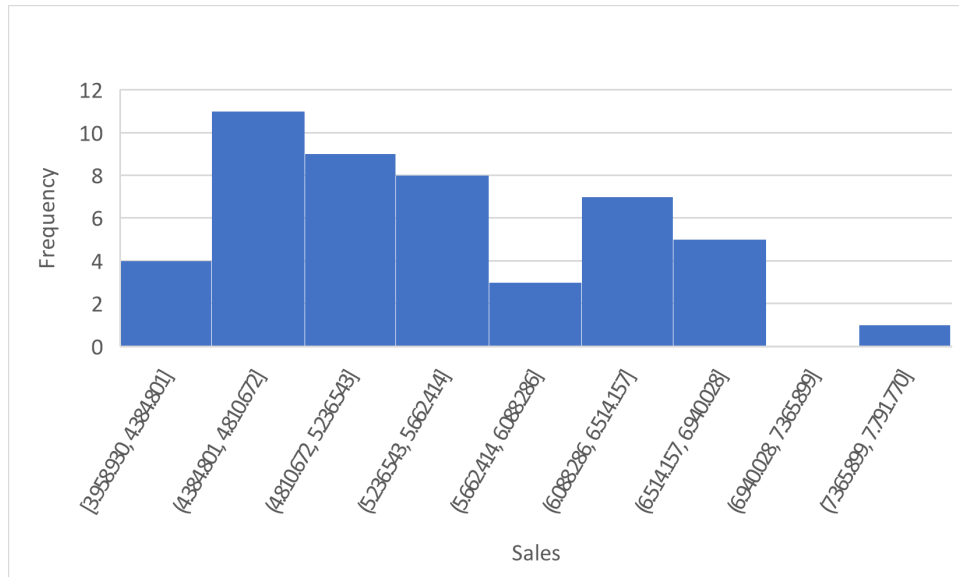


Figure 13, “Histogram of Pilsner sales”

The histogram for **Pilsner** sales illustrates the frequency distribution of monthly sales amounts, grouping them into sales intervals. This visualization shows that the majority of **Pilsner** sales fall within the middle ranges, around 4.8 million to 6.5 million, with the most frequent range being between 4.8 million and 5.2 million. There is a rightward skew in the histogram, indicated by the presence of higher sales values on the far right, although these occur less frequently. This skew aligns with the descriptive statistics, which showed a slight positive skewness, confirming that most sales values cluster around the lower-to-middle range with fewer high sales values. This distribution suggests that while high sales months do occur, they are relatively rare, with most months experiencing moderate sales levels.

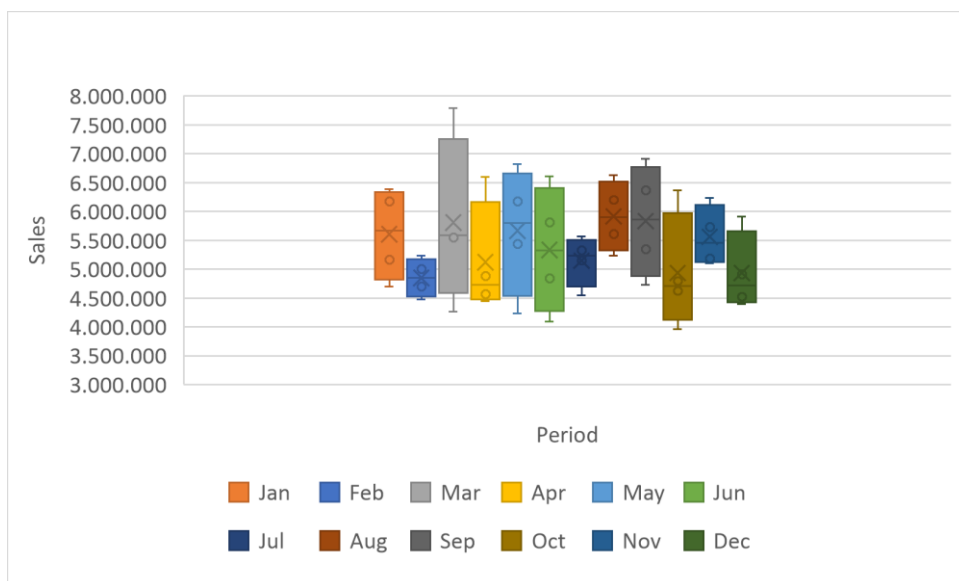


Figure 14, “Monthly Boxplot of Pilsner sales”

The box plot for **Pilsner** sales reveals insights into monthly variability and seasonal trends. Postgraduate Dissertation

Most months show a relatively narrow interquartile range, suggesting stable sales with moderate consistency. However, some months have taller boxes and extended whiskers, indicating wider variability and occasional spikes or drops in sales, which aligns with the slightly positive skewness observed in the descriptive statistics. Higher medians in certain months suggest seasonal peaks, where demand for **Pilsner** likely increases, possibly due to seasonal events or promotional campaigns. Overall, the plot suggests a recurring demand cycle with predictable fluctuations, but with no extreme outliers, indicating that sales, while variable, remain within an expected range throughout the year.

Product **Porter**

Following the same process, **Figures 15, 16 and 17** respectively display the time series plot, histogram and boxplot for product **Porter**.

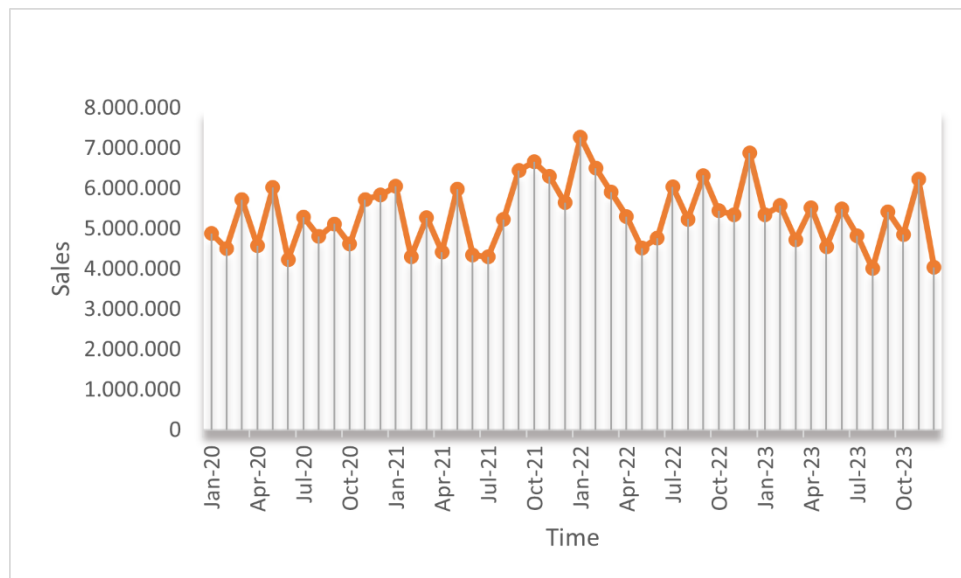


Figure 15, “Time series plot of Porter sales 2020-2023”

The time series plot of **Porter**’s sales shows a consistent fluctuation over the 48-month period, from January 2020 to December 2023. There are visible seasonal patterns, with peaks occurring around mid-year (July-August) and dips typically observed towards the end of the year (October-November). The sales trend appears stable overall, without drastic increases or declines, indicating consistent performance. However, the observed fluctuations suggest possible influences of seasonality, where certain months may correspond to higher demand periods.

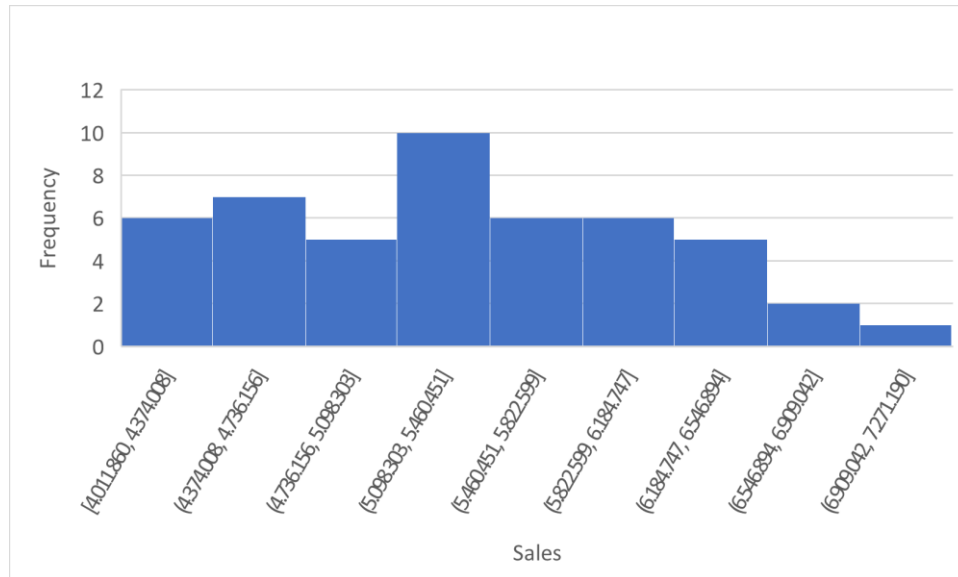


Figure 16, “Histogram of Porter sales”

The histogram of sales data provides insights into the distribution pattern of **Porter**’s sales. The sales data appears relatively normally distributed with a slight right skew (as indicated by a positive skewness of 0.31). Most sales values cluster between approximately 4.3 million and 5.5 million, with fewer occurrences of extremely high sales values, as indicated by the right tail extending towards 7.3 million. This suggests that while the bulk of sales are consistent, there are occasional peaks that push the sales figures higher.

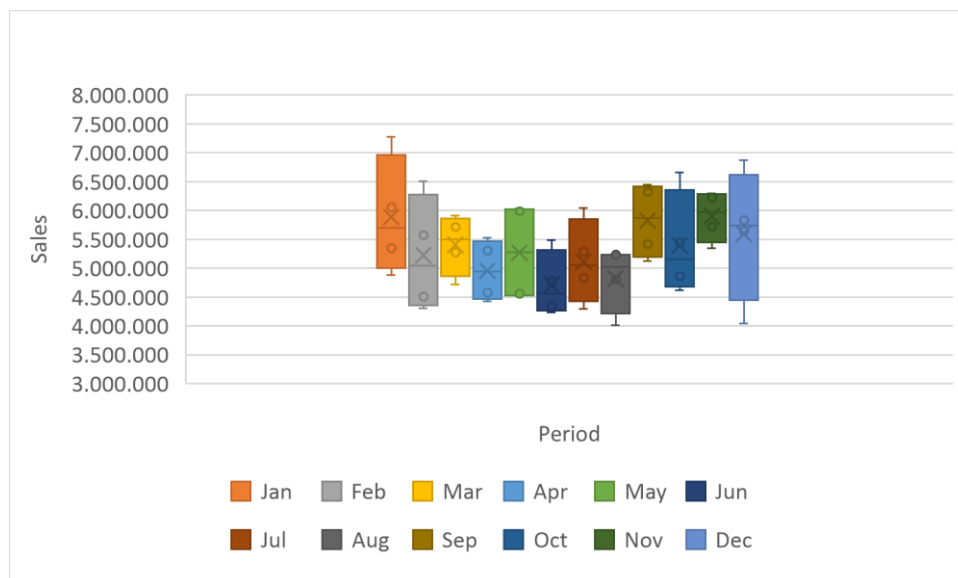


Figure 17, “Monthly Boxplot of Porter sales”

The box plot reveals the monthly distribution of **Porter**’s sales across the period analyzed. The data distribution across the months shows considerable variability, as indicated by the range of the interquartile ranges (IQRs). While some months, like January and December, have wider boxes and larger whiskers, suggesting higher variability, others like March and

May show less spread, indicating more consistent sales performance. Outliers are present in some months, which may indicate exceptionally high or low sales figures due to specific external factors or anomalies.

Product **Sour**

Building on the visual analysis of the previous products, **Figures 18, 19** and **20** respectively illustrate the time series plot, histogram and boxplot for product **Sour**.

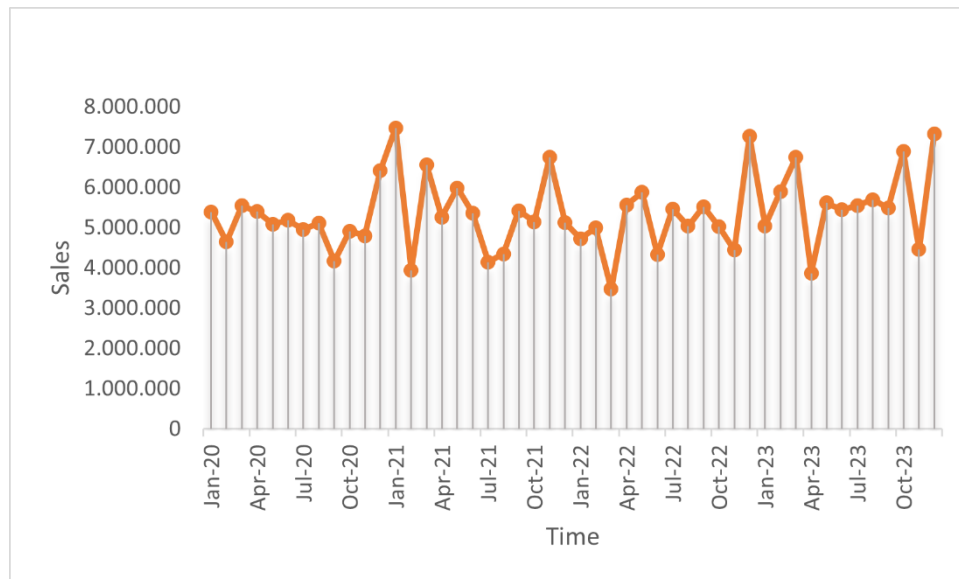


Figure 18, “Time series plot of Sour sales 2020-2023”

The time series plot for **Sour**’s sales illustrates a pattern of consistent fluctuations over time, with some notable peaks and valleys. This pattern suggests a degree of seasonality or recurring market conditions that impact monthly sales. Although there are regular ups and downs, the sales values tend to return to a central level around the mean, indicating that **Sour**’s market performance is stable without any dramatic growth or decline trends over the observed period. This stability reflects a reliable demand for the product, with periodic variations that may be linked to specific times of the year or market events.

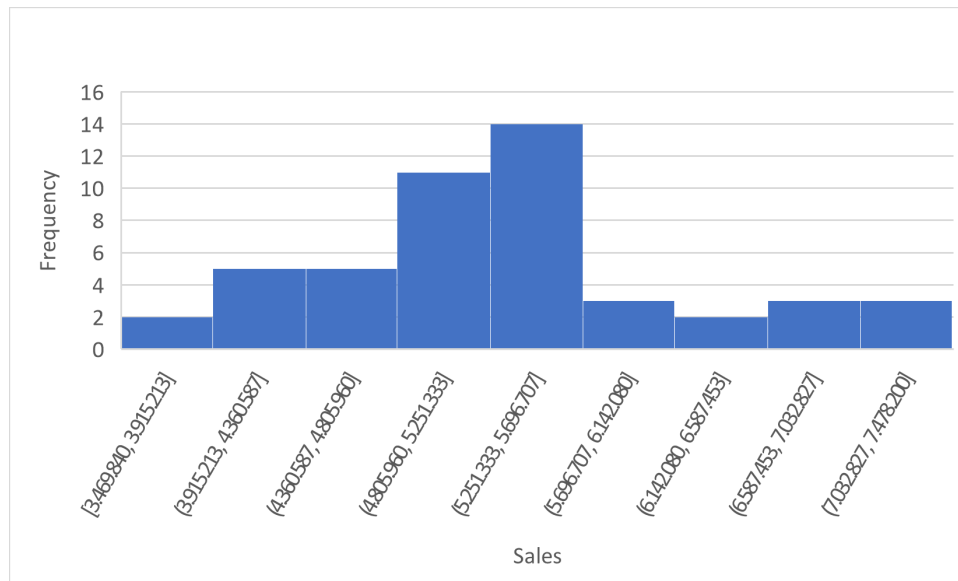


Figure 19, “Histogram of Sour sales”

The histogram shows the frequency distribution of sales figures for **Sour**, revealing that most sales data points fall within the 4.8 million to 6.2 million range. This central clustering indicates that typical monthly sales are concentrated around this middle range, with only a few months reaching particularly high or low sales figures. The histogram is slightly skewed to the right, which aligns with the positive skew seen in the descriptive statistics. This suggests that while higher sales are less frequent, they do occasionally occur.

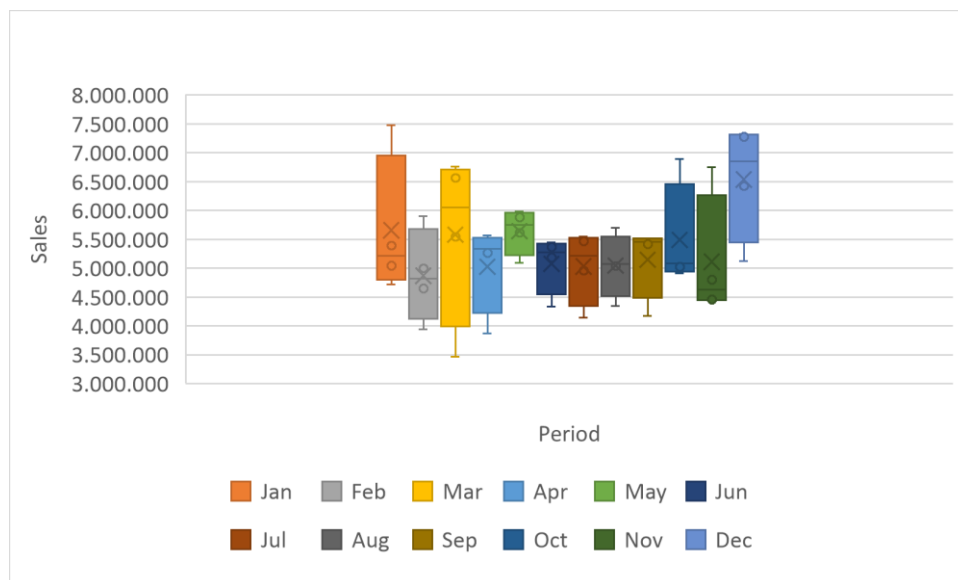


Figure 20, “Monthly Boxplot of Sour sales”

The box plot provides a monthly breakdown of sales data for **Sour**, highlighting the range, median and spread of sales figures. Most months display relatively symmetrical distributions, meaning sales are fairly consistent month to month. However, certain months have a wider spread, indicating periods of greater variability in sales, while others are narrower, reflecting

more stable sales volumes. The absence of significant outliers in the box plot suggests that extreme sales figures are uncommon, reinforcing the idea of consistent performance. Overall, this chart implies that while **Sour** experiences some variability, sales largely remain within a predictable range.

Product Stout

This study will adopt a comparable method to evaluate the sales attributes of product **Stout**, which falls within the same category as the previously examined products. The primary goal is to analyze sales patterns, particularly the consistency of the mean and variance over the recorded years. To support this assessment, visual representations—including a time series plot, histogram and boxplot—will be utilized to detect potential outliers in the dataset. **Figures 21, 22 and 23** showcase these respective charts.

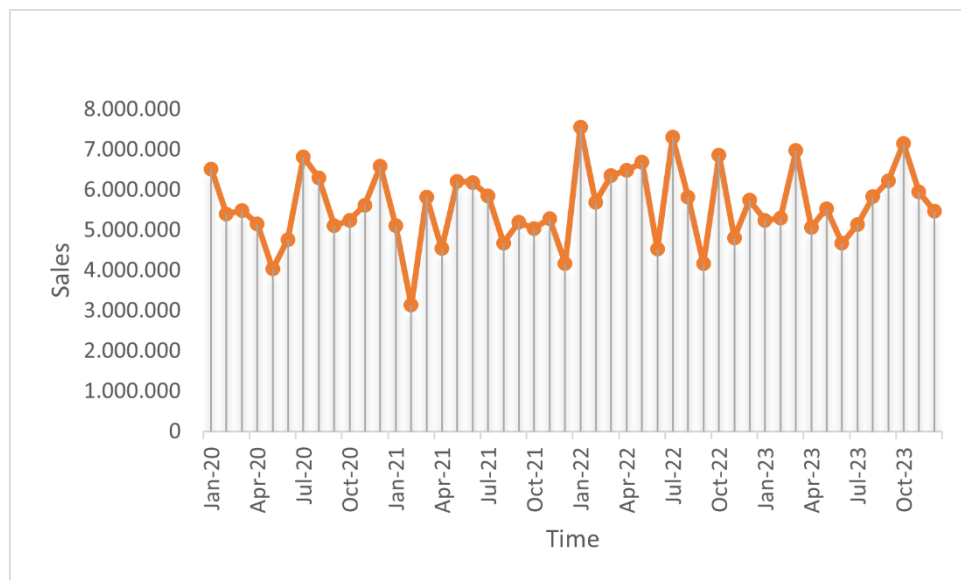


Figure 21, “Time series plot of Stout sales 2020-2023”

The time series plot shows the trend of **Stout**’s sales over time, revealing a clear seasonal pattern with regular peaks and troughs. Sales appear to rise and fall in a cyclical manner, suggesting periodic demand changes, likely tied to seasonal factors or promotional cycles. While there are fluctuations, the overall trend remains consistent, with no drastic deviations, reflecting the stable range observed in the descriptive statistics. The spikes at regular intervals indicate opportunities where the company experiences increased sales, which could be leveraged further to optimize marketing strategies and smoothen sales during off-peak periods.

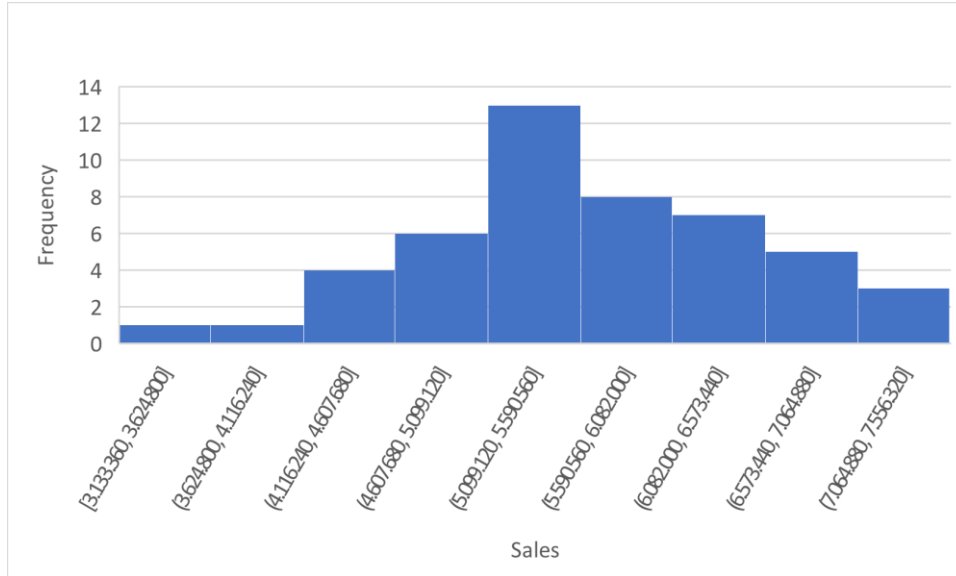


Figure 22, “Histogram of Stout sales”

The histogram displays the frequency distribution of **Stout**’s sales, showing how often sales fall within specific ranges. The majority of sales lie between 5,099,120 and 6,573,440, indicating that mid-level sales are the most frequent. The bell-shaped pattern suggests a normal distribution, with fewer instances of extremely high or low sales. This is consistent with the descriptive statistics showing a kurtosis of 0.01, indicating that the data does not have heavy tails or extreme deviations from the mean. The symmetry of the histogram aligns with the skewness near zero, confirming that sales distribution is balanced and lacks significant outliers.

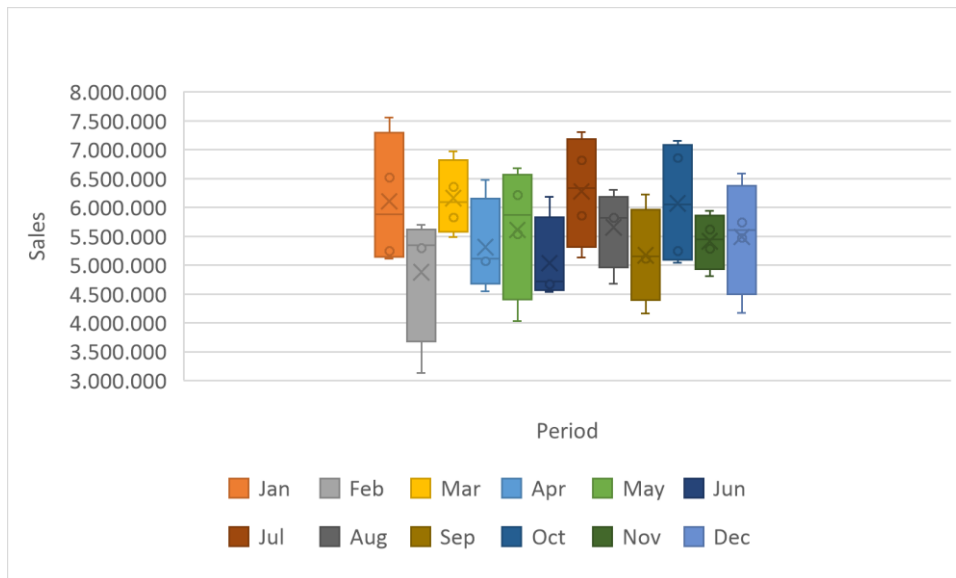


Figure 23, “Monthly Boxplot of Stout sales”

The box plot illustrates the monthly variability in Stout’s sales, with each box representing the spread of sales for a given month. The interquartile ranges (IQRs) vary, indicating that

some months experience more consistent sales while others have greater fluctuation. Notably, the medians (middle line in each box) are fairly stable across months, which suggests that sales follow a consistent pattern throughout the year. There are no apparent outliers, indicating that sales remain within a predictable range, and the data distribution is relatively symmetrical. This aligns with the descriptive statistics showing a low skewness value (-0.08), suggesting that the data is neither heavily skewed to the left nor right.

Product **Wheat Beer**

Lastly, **Figures 24-26** provide a visual summary for the final product, **Wheat Beer**, following the same analytical framework and methodology applied to the previous products.

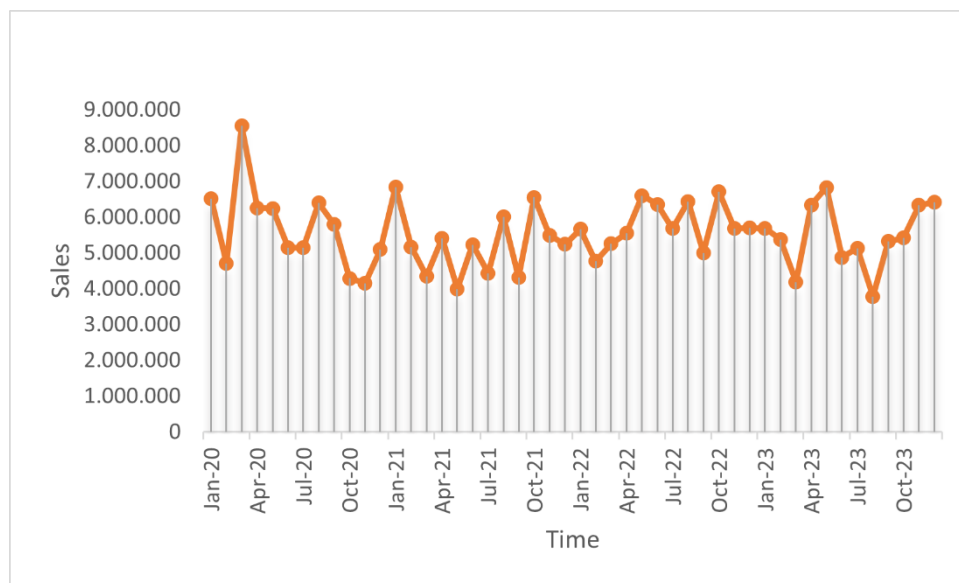


Figure 24, “Time series plot of Wheat Beer sales 2020-2023”

The time series plot of **Wheat Beer** sales reveals a pattern of fluctuations over time, with occasional peaks and troughs. Seasonal trends may be inferred, as some of the spikes and dips seem to recur at regular intervals. Early in the timeline, there is higher variability in sales, with sharper peaks and deeper troughs, but later periods appear more stable. Despite the fluctuations, the sales remain within a relatively defined range, with the maximum sales reaching 8.550.000 and the minimum at 3.785.700. This graph underscores the importance of understanding time-based patterns, which can be leveraged for better forecasting and inventory management during high-demand periods.

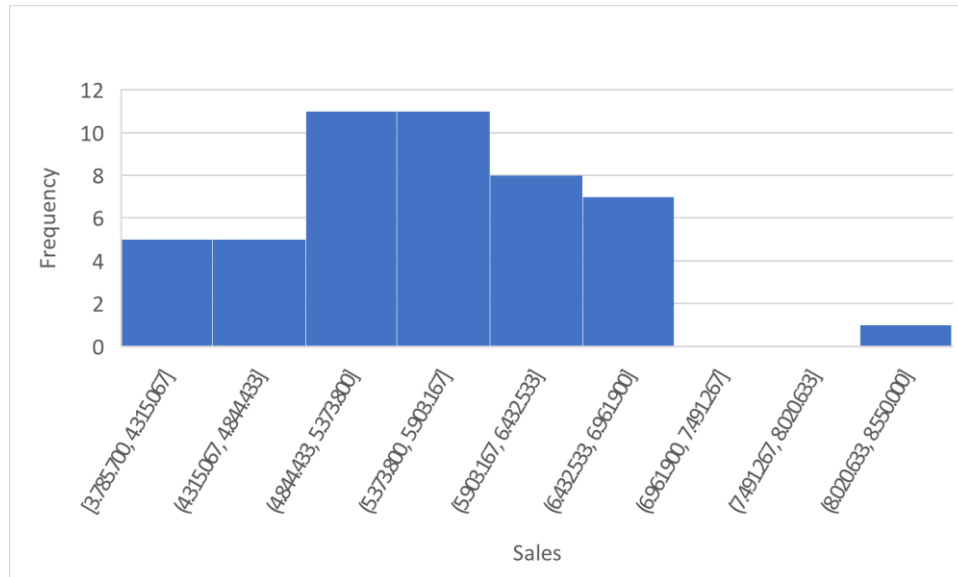


Figure 25, “Histogram of Wheat Beer sales”

The histogram provides a clear view of the distribution of **Wheat Beer** sales, showing that most data points fall within the range of 4,800,000 to 6,600,000. The shape of the histogram reveals a slight right skew, with the bulk of sales clustered around the mean (5,553,390). This is consistent with the descriptive statistics, including a positive skewness value (0.46). While sales values are generally concentrated around the mean, the distribution has a few higher values, suggesting occasional surges in demand. The moderate spread, indicated by the standard deviation of 929,056, reflects variability while still showing a well-defined central tendency.

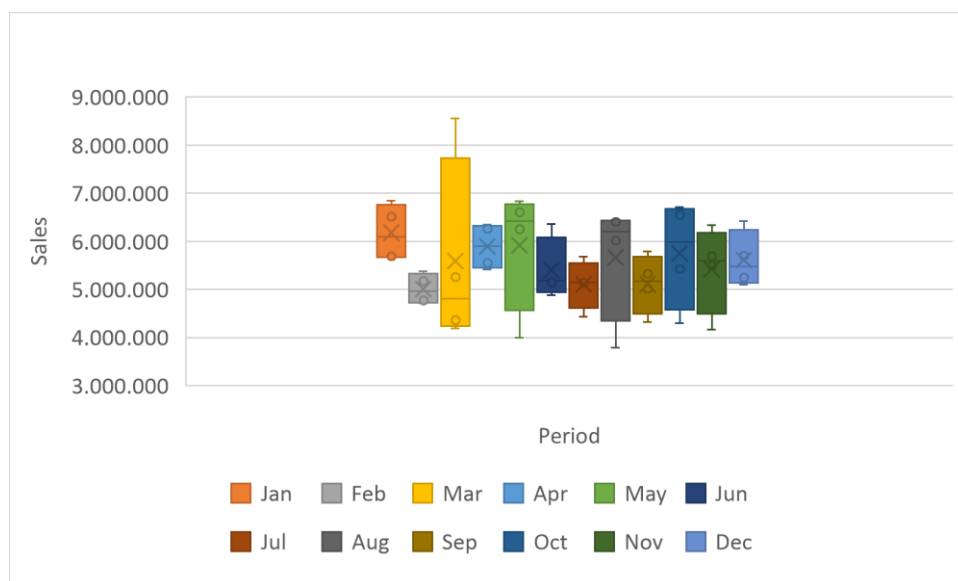


Figure 26, “Monthly Boxplot of Wheat Beer sales”

The box plot for **Wheat Beer** sales highlights monthly variations in sales performance. March stands out with the highest variability, as reflected by its significantly larger range compared

to other months. The interquartile ranges (IQR) for most months are relatively narrow, suggesting consistent sales for a majority of the time. The median sales value is slightly below the mean, which aligns with the slightly skewed nature of the data. Outliers are present in some months, indicating occasional extreme sales events, either significantly higher or lower than the norm. These outliers and variability might reflect seasonal factors or unique promotional events driving sales trends.

4.3 Stylized Facts of the Demand for Beer Products

To analyze the statistical properties of the product dataset over time and determine the most appropriate regression model, a stepwise regression analysis will be performed. This approach will include relevant variables such as monthly dummy indicators to capture potential seasonal effects, trend components (linear or quadratic) and autoregressive elements with lagged variables to identify short- or long-term sales dependencies. Additionally, the analysis will account for interactions between the datasets of different products and consider the potential influence of the Covid-19 pandemic using a specific dummy variable. This methodology aims to address the research questions set out in Chapter 1.4.

The regression model to be employed for examining the features of each product's sales data can be represented by the following equation:

$$M_1: S_t = \beta_0 + \gamma_0 t + \gamma_1 t^2 + \sum_{i=1}^{11} \beta_i M_{t,i} + \sum_{j=1}^2 \delta_j S_{t-j} + e_t \quad (4.2.1)$$

where, β_0 is the constant term (intercept) of the time series corresponding to effect of the baseline month December, γ_0 and γ_1 are the slope coefficients of the linear and quadratic trend respectively, β_i is the coefficient of each monthly dummy variables $M_{t,i}$ where $i = \{1, 2, \dots, 11\}$, δ_j is the coefficient of each lag variables S_{t-j} where $j = \{1, 2\}$ and e_t is the disturbance or error term.

Monthly dummy variables are a common element in statistical analysis, employed to capture seasonal patterns and month-specific variations within the data. In this context, “dummies” refer to binary indicators for each month, which take the value of 1 for observations corresponding to a particular month and 0 otherwise. By incorporating these variables, the model can account for systematic differences across the months. Including monthly dummies in a regression model allows the estimation of the average impact of each month on the dependent variable, while controlling for other factors. To avoid the problem of perfect multicollinearity, which can distort model estimates and hinder predictive accuracy, one month is consistently excluded from the model as the baseline or reference category. This

approach will be applied across the entire dataset from 2020 to 2023 for all eight products under study.

In the context of Multiple Linear Regression (MLR) analysis, the decision to include or exclude an explanatory variable hinges on hypothesis testing to determine the statistical significance of its associated regression coefficient. The primary criterion involves assessing whether the coefficient β_i is equal to zero, indicating that the variable does not contribute explanatory power to the model. This evaluation is typically carried out using a two-tailed test based on the t -distribution. The null hypothesis ($H_0: \beta_i = 0$) implies that the coefficient is not significant, whereas the alternative hypothesis ($H_1: \beta_i \neq 0$) suggests that it is significant.

The position of the test statistic under the null hypothesis plays a crucial role in inference. If the test statistic falls in the extreme tails of the distribution, it may indicate a contradiction with the null hypothesis. Conversely, a statistic closer to the center suggests consistency with it. The p-value, derived from the distribution of the test statistic, quantifies the probability of observing such an extreme value purely by chance, assuming the null hypothesis is true. This p-value, also known as the significance level, is used to determine the strength of evidence against the null hypothesis. When the p-value is below the threshold of 0.05, it indicates statistical significance at the 95% confidence level, providing strong evidence against the null hypothesis (Kutner et al., 2005).

4.4 Sales data transformation into logarithmic set

The initial step in this analysis involves transforming the sales time series data using natural logarithms, which can be performed in Excel using the LN function. This transformation is often advantageous, as it helps mitigate certain problematic characteristics in the dataset that could otherwise skew the results of the analysis. Feng et al. (2014) highlight that applying logarithmic transformations in regression models is a common approach, particularly when dealing with non-linear relationships between the independent and dependent variables. Using the logarithmic form of variables, rather than their raw values, helps introduce a non-linear association while still maintaining the linear structure of the model.

According to Chatterjee and Hadi (2012), logarithmic transformations provide several key benefits: they help to normalize skewed data distributions, stabilize the variance across observations, linearize the relationships between variables (making them more suitable for linear regression analysis), handle outliers more effectively and improve the interpretability

of the results when expressed in log terms. Due to these advantages, the sales time series for each product were converted using natural logarithms before moving on to further explanatory and predictive modeling. Consequently, the previous model M_1 , as defined in equation (4.2.1), was reformulated using the logarithmic transformation.

$$M_1: \log(S_t) = \beta_0 + \gamma_0 t + \gamma_1 t^2 + \sum_{i=1}^{11} \beta_i M_{t,i} + \sum_{j=1}^2 \delta_j \log(S_{t-j}) + e_t \quad (4.3.1)$$

where, $\log(S_t)$ is the logarithm of the observed sales S_t , β_0 is the constant term (intercept) of the time series corresponding to effect of the baseline month December, γ_0 and γ_1 are the slope coefficients of the linear and quadratic trend respectively, β_i is the coefficient of each monthly dummy variables $M_{t,i}$ where $i = \{1, 2, \dots, 11\}$, δ_j is the coefficient of each lag variables S_{t-j} where $j = \{1, 2\}$ and e_t is the disturbance or error term.

4.5 Statistical significance of the explanatory variables in MLR model

The application of regression model M_1 to the sales time series of each product aims to investigate the relationship between the dependent variable and the various independent variables. The significance of each predictor will be evaluated using the p-values generated from the regression analysis output. These p-values help determine the contribution of each explanatory variable in explaining the variation in the dependent variable. As discussed in Chapter 4.2, the null hypothesis (H_0) is rejected if the p-value is less than the chosen significance level (α), which is set at 0.05 (95% confidence level) in this analysis. This indicates that the coefficient β_i is significantly different from zero. If the p-value is greater than or equal to α , we do not have sufficient evidence to reject (H_0) in favor of the alternative hypothesis (H_1).

This procedure will be consistently applied to assess the significance of each independent variable, including monthly dummy variables, autoregressive lag terms, cross-dependency factors and the Covid-19 pandemic dummy variable used in the MLR models. By following this structured approach, the research objectives outlined in Chapter 1.4 will be systematically addressed and the findings will be clearly presented and interpreted.

4.5.1 Statistical Properties of product **Ale**

Starting with product **Ale**, the implementation of the M_1 multiple linear regression (MLR) model, as described earlier, seeks to provide meaningful insights into the statistical properties of the product's sales time series. This analysis also aims to evaluate the significance of the explanatory variables included in the model. The regression summary results generated using

Excel are displayed below in **Table 6**.

Term	Coefficients	Standard Error	T Stat	P-Value
Intercept	22.4745	3.5131	6.3974	0.0000
Linear Trend	-0.0097	0.0070	-1.3873	0.1749
Quadratic Trend	0.0002	0.0001	1.1521	0.2578
M_{t1}	0.0869	0.1166	0.7455	0.4614
M_{t2}	-0.0261	0.1169	-0.2229	0.8251
M_{t3}	-0.1226	0.1176	-1.0425	0.3050
M_{t4}	-0.0928	0.1174	-0.7905	0.4350
M_{t5}	0.0432	0.1159	0.3730	0.7116
M_{t6}	-0.1170	0.1157	-1.0110	0.3196
M_{t7}	0.0698	0.1187	0.5881	0.5606
M_{t8}	-0.0225	0.1141	-0.1975	0.8447
M_{t9}	-0.0336	0.1149	-0.2921	0.7721
M_{t10}	-0.0607	0.1148	-0.5287	0.6006
M_{t11}	-0.0167	0.1144	-0.1463	0.8846
Lag Variable t-1	0.0048	0.1583	0.0300	0.9762
Lag Variable t-2	-0.4478	0.1606	-2.7886	0.0088

Table 6 “Regression summary with monthly dummies and lag variables for product Ale”

The summary output reveals that both the linear and quadratic trend components are not statistically significant, as their p-values are considerably higher than the critical threshold of $\alpha = 0.05$, which corresponds to a 5% significance level. This finding aligns with the no-trend pattern illustrated in **Figure 3**, as well as the analysis discussed in Chapter 4.2.1 and summarized in **Table 3**. Similarly, the coefficients for the monthly dummy variables ($M_{t,i}$) also exhibit a lack of statistical significance, indicating the absence of any apparent seasonality in the dataset.

On the other hand, the lag variable ($t - 2$) has a low p-value, suggesting that there is a short-memory effect present in the sales time series. This implies that the demand for the product does not fully dissipate within the same period but continues to influence sales in the subsequent two periods. This insight could be particularly valuable for company decision-makers and sales managers, as it offers useful information for optimizing inventory management strategies.

4.5.2 Statistical Properties of product **IPA**

Applying the M_1 regression model to product **IPA** aims to explore the unique characteristics of its sales time series and examine the significance of the independent variables in

explaining the dependent variable's behavior. This analysis allows for a comparative assessment, shedding light on how the model's effectiveness and the relevance of variables may vary between different products. The summary results generated from Excel's regression analysis are shown in **Table 7** below.

Term	Coefficients	Standard Error	T Stat	P-Value
Intercept	24.6104	4.5359	5.4257	0.0000
Linear Trend	0.0094	0.0078	1.2012	0.2385
Quadratic Trend	-0.0002	0.0002	-1.2729	0.2122
M_{t1}	0.0004	0.1321	0.0028	0.9978
M_{t2}	-0.2409	0.1303	-1.8492	0.0737
M_{t3}	-0.0390	0.1280	-0.3043	0.7629
M_{t4}	-0.1445	0.1348	-1.0722	0.2916
M_{t5}	-0.1269	0.1267	-1.0013	0.3242
M_{t6}	-0.1974	0.1283	-1.5388	0.1337
M_{t7}	-0.1742	0.1268	-1.3743	0.1789
M_{t8}	-0.0865	0.1282	-0.6745	0.5048
M_{t9}	-0.1891	0.1277	-1.4809	0.1484
M_{t10}	-0.0695	0.1257	-0.5525	0.5844
M_{t11}	-0.1687	0.1294	-1.3037	0.2017
Lag Variable t-1	-0.4354	0.1760	-2.4740	0.0189
Lag Variable t-2	-0.1484	0.1764	-0.8411	0.4066

Table 7 “Regression summary with monthly dummies and lag variables for product IPA”

The evaluation of the regression output from the M_1 model for product **IPA** indicates that the null hypothesis (H_0) cannot be rejected for the coefficients of the monthly dummy variables, suggesting there is no evidence of seasonality in the sales data. Similarly, the p-values for both the linear and quadratic trend components do not indicate statistical significance.

Furthermore, the significant low p-value for the lag variable ($t - 1$) suggests a short-term memory effect in the sales time series, indicating that current sales levels are influenced by observations from the previous period. This finding implies a persistence or momentum effect in sales, which should be factored into the company's strategic planning and inventory decisions.

4.5.3 Statistical Properties of product **Lager**

The analysis now proceeds with product **Lager**, utilizing the regression summary output in a manner consistent with the previous products. The findings from the application of the M_1

regression model to the sales time series of product **Lager**, including the monthly dummy variables and lag terms, are summarized in **Table 8**.

Term	Coefficients	Standard Error	T Stat	P-Value
Intercept	31.1275	4.3911	7.0888	0.0000
Linear Trend	-0.0023	0.0057	-0.4059	0.6875
Quadratic Trend	0.0000	0.0001	0.1811	0.8574
M _{t1}	0.0768	0.0990	0.7758	0.4435
M _{t2}	-0.0488	0.0977	-0.4995	0.6209
M _{t3}	0.0715	0.0980	0.7299	0.4708
M _{t4}	0.0463	0.0970	0.4773	0.6364
M _{t5}	0.0955	0.0958	0.9969	0.3263
M _{t6}	0.1850	0.0954	1.9392	0.0613
M _{t7}	0.2027	0.0968	2.0941	0.0443
M _{t8}	0.2783	0.0984	2.8294	0.0080
M _{t9}	0.1454	0.0987	1.4733	0.1504
M _{t10}	0.0910	0.0973	0.9347	0.3569
M _{t11}	0.0662	0.0952	0.6957	0.4916
Lag Variable t-1	-0.5905	0.1667	-3.5432	0.0012
Lag Variable t-2	-0.4206	0.1676	-2.5101	0.0173

Table 8 “Regression summary with monthly dummies and lag variables for product Lager”

The regression analysis clearly reveals a seasonal effect in the sales time series of product **Lager**. The p-values for the coefficients of the monthly dummy variables corresponding to the summer months, specifically July and August, are notably below the 0.05 threshold, indicating a strong seasonal influence during this period. Additionally, for the month of June, it’s worth noting that while the coefficient does not appear significant at the 5% level, there is evidence of a potential significance at the 10% level. This seasonal pattern had been previously noted in the graphical analysis of product **Lager** in Chapter 4.2.1, and was further confirmed by the product’s histogram in **Figure 10**, which visually highlighted increased sales during the summer months, consistent with the results from the regression model.

Further examination shows that the high p-values for the linear and quadratic trend coefficients suggest a lack of a significant trend, reinforcing earlier findings from Chapter 4.2.1, where no consistent increase or decrease over time was observed in the graphical summaries. In contrast, the low p-values for the lagged variables indicate that the sales time series exhibits short-term memory effects. This suggests that past sales data have a statistically significant impact on current sales, as shown by the autoregressive coefficients in **Table 8**, implying that recent sales observations are relevant for predicting future demand.

4.5.4 Statistical Properties of product **Pilsner**

The same analytical approach used for previous products was applied to product **Pilsner**, in order to assess the results from the M_1 regression model. The output summary, presented in **Table 9**, includes the findings from the multiple linear regression analysis, incorporating linear and quadratic trend components, as well as monthly dummy variables and lag terms.

Term	Coefficients	Standard Error	T Stat	P-Value
Intercept	18.8853	4.1126	4.5921	0.0001
Linear Trend	0.0014	0.0072	0.1986	0.8438
Quadratic Trend	0.0000	0.0001	0.0787	0.9378
M_{t1}	0.1407	0.1244	1.1311	0.2664
M_{t2}	0.0092	0.1215	0.0759	0.9400
M_{t3}	0.1585	0.1252	1.2659	0.2147
M_{t4}	0.0507	0.1210	0.4187	0.6782
M_{t5}	0.1456	0.1247	1.1675	0.2516
M_{t6}	0.0859	0.1209	0.7106	0.4825
M_{t7}	0.0618	0.1232	0.5020	0.6191
M_{t8}	0.1891	0.1215	1.5561	0.1295
M_{t9}	0.1838	0.1213	1.5159	0.1394
M_{t10}	0.0195	0.1255	0.1550	0.8778
M_{t11}	0.1234	0.1252	0.9855	0.3318
Lag Variable t-1	-0.1378	0.1779	-0.7748	0.4442
Lag Variable t-2	-0.0907	0.1778	-0.5099	0.6136

Table 9 “Regression summary with monthly dummies and lag variables for product Pilsner”

The elevated p-values for the coefficients of the linear and quadratic trends indicate that there is no significant trend present in the sales time series for this product. This finding is consistent with the visual representation of the time series shown in **Figure 12** and is further backed by the detailed analysis of the product’s attributes discussed in Chapter 4.2.1.

In addition, the high p-values for the other explanatory variables, particularly those related to seasonality (monthly dummy variables) and autoregressive (lag) terms, suggest the absence of both seasonal patterns and short-term memory effects in the product’s sales data.

4.5.5 Statistical Properties of product **Porter**

The next stage of the analysis focuses on product **Porter**, with the results obtained from applying the MLR model M_1 using Excel’s formulas and functions summarized in **Table 10** below.

Term	Coefficients	Standard Error	T Stat	P-Value
Intercept	17.3091	4.2314	4.0907	0.0003
Linear Trend	0.0178	0.0068	2.6063	0.0138
Quadratic Trend	-0.0004	0.0001	-2.6745	0.0117
M _{t1}	0.0615	0.1004	0.6122	0.5447
M _{t2}	-0.0730	0.1014	-0.7192	0.4772
M _{t3}	-0.0511	0.1022	-0.5002	0.6204
M _{t4}	-0.1271	0.0998	-1.2734	0.2120
M _{t5}	-0.0905	0.1032	-0.8771	0.3870
M _{t6}	-0.1856	0.1018	-1.8222	0.0778
M _{t7}	-0.1279	0.1068	-1.1972	0.2400
M _{t8}	-0.1649	0.1052	-1.5667	0.1270
M _{t9}	0.0123	0.1057	0.1167	0.9078
M _{t10}	-0.0321	0.0998	-0.3219	0.7496
M _{t11}	0.0436	0.1001	0.4355	0.6661
Lag Variable t-1	-0.1754	0.1837	-0.9549	0.3468
Lag Variable t-2	0.0513	0.1853	0.2768	0.7837

Table 10 “Regression summary with monthly dummies and lag variables for product Porter”

The regression summary results show that most coefficients are not statistically significant indicating that seasonality is not present in the time series. However, it’s worth noting that while the coefficient associated with the dummy variable for June, does not appear significant at the 5% level, there is evidence of a potential significance at the 10% significance level. Additionally, the high p-values of the lag variables, exceeding the significance level of $\alpha = 0.05$, suggest that the current product’s time series does not exhibit any short-term memory effect.

Conversely, the p-values for both the linear and quadratic trend components indicate statistical significance. The positive coefficient of the linear trend points to a steady increase in sales over time, while the slight negative coefficient of the quadratic trend hints at a gradual deceleration in this growth.

4.5.6 Statistical Properties of product **Sour**

The analysis now moves on to product **Sour**, with the results summarized in **Table 11**. The M_1 model applied to the sales time series includes elements like time trends, autoregressive terms and monthly dummy variables, following a similar approach to that used in the evaluation of previous products.

Term	Coefficients	Standard Error	T Stat	P-Value
Intercept	22.2694	4.4120	5.0474	0.0000

Linear Trend	-0.0072	0.0073	-0.9836	0.3327
Quadratic Trend	0.0002	0.0001	1.3324	0.1922
M _{t1}	-0.0608	0.1266	-0.4804	0.6342
M _{t2}	-0.2217	0.1265	-1.7527	0.0892
M _{t3}	-0.1667	0.1201	-1.3874	0.1749
M _{t4}	-0.2286	0.1213	-1.8840	0.0687
M _{t5}	-0.1212	0.1195	-1.0141	0.3182
M _{t6}	-0.1990	0.1213	-1.6401	0.1108
M _{t7}	-0.2356	0.1196	-1.9699	0.0576
M _{t8}	-0.2481	0.1195	-2.0756	0.0461
M _{t9}	-0.2328	0.1197	-1.9452	0.0606
M _{t10}	-0.1688	0.1195	-1.4128	0.1674
M _{t11}	-0.2284	0.1197	-1.9082	0.0654
Lag Variable t-1	-0.3226	0.1758	-1.8354	0.0757
Lag Variable t-2	-0.1034	0.1796	-0.5759	0.5687

Table 11 “Regression summary with monthly dummies and lag variables for product Sour”

The regression analysis highlights a clear seasonal pattern in the sales time series for product **Sour**. Specifically, the p-value for the coefficient associated with the August dummy variable falls below the 0.05 threshold, confirming a significant seasonal impact during this month. Additionally, while the coefficients for February, April, July, September and December are not statistically significant at the 5% level, they demonstrate potential significance at the 10% level.

Further analysis reveals that the high p-values for both the linear and quadratic trend coefficients suggest the absence of a notable trend, consistent with the findings in Chapter 4.2.1, where the graphical analysis showed no sustained upward or downward trajectory over time. Similarly, the p-values for the lagged variables indicate that the sales data lacks evidence of short-term memory effects.

4.5.7 Statistical Properties of product **Stout**

The analysis now shifts to product **Stout**, with the results from applying the MLR model M_1 using Excel’s functions and formulas presented in **Table 12** below.

Term	Coefficients	Standard Error	T Stat	P-Value
Intercept	15.4200	3.6923	4.1990	0.0002
Linear Trend	-0.0005	0.0077	-0.0656	0.9481
Quadratic Trend	0.0000	0.0002	0.3247	0.7475
M _{t1}	0.1134	0.1309	0.8666	0.3926
M _{t2}	-0.1263	0.1308	-0.9559	0.3413

M_{t3}	0.1535	0.1298	1.1827	0.2457
M_{t4}	-0.0422	0.1367	-0.3086	0.7594
M_{t5}	0.0362	0.1280	0.2831	0.7789
M_{t6}	-0.0808	0.1296	-0.6234	0.5374
M_{t7}	0.1485	0.1286	1.1549	0.2567
M_{t8}	0.0189	0.1341	0.1411	0.8887
M_{t9}	-0.0507	0.1277	-0.3970	0.6940
M_{t10}	0.1056	0.1278	0.8266	0.4146
M_{t11}	-0.0241	0.1317	-0.1827	0.8562
Lag Variable t-1	0.0853	0.1744	0.4893	0.6280
Lag Variable t-2	-0.0817	0.1744	-0.4686	0.6425

Table 12 “Regression summary with monthly dummies and lag variables for product Stout”

The regression summary results show similarities between the sales patterns of product **Pilsner** and product **Stout**. The high p-values for both the linear and quadratic trend coefficients suggest the absence of any significant trend within the sales data for this product.

Additionally, the elevated p-values for the seasonal dummy variables and autoregressive terms imply a lack of seasonal fluctuations and short-term memory effects in the product’s sales data, indicating that neither seasonality nor past sales significantly influence current sales levels.

4.5.8 Statistical Properties of product **Wheat Beer**

The final phase of the analysis examines product **Wheat Beer**, focusing on the presence of linear and quadratic trends, seasonal influences and autoregressive factors. The summary results of the M_1 regression model are detailed in **Table 13** below.

Term	Coefficients	Standard Error	T Stat	P-Value
Intercept	12.3632	3.7072	3.3349	0.0022
Linear Trend	-0.0078	0.0079	-0.9933	0.3280
Quadratic Trend	0.0002	0.0002	1.0378	0.3071
M_{t1}	0.1243	0.1342	0.9258	0.3615
M_{t2}	-0.1043	0.1337	-0.7798	0.4413
M_{t3}	-0.0505	0.1319	-0.3829	0.7043
M_{t4}	0.0738	0.1320	0.5590	0.5801
M_{t5}	0.0446	0.1315	0.3394	0.7365
M_{t6}	-0.0445	0.1307	-0.3402	0.7359
M_{t7}	-0.0944	0.1298	-0.7279	0.4720
M_{t8}	0.0051	0.1301	0.0392	0.9689

M_{t9}	-0.0759	0.1310	-0.5798	0.5661
M_{t10}	0.0202	0.1297	0.1554	0.8775
M_{t11}	-0.0267	0.1310	-0.2034	0.8401
Lag Variable t-1	0.0466	0.1744	0.2672	0.7910
Lag Variable t-2	0.1616	0.1734	0.9320	0.3583

Table 13 “Regression summary with monthly dummies and lag variables for product Wheat Beer”

The regression summary reveals parallels in the sales patterns of product **Stout** and product **Wheat Beer**. The elevated p-values for both the linear and quadratic trend coefficients indicate that no significant trend is present in the sales data for either product.

Moreover, the high p-values associated with the seasonal dummy variables and autoregressive terms suggest an absence of seasonal variation and short-term dependencies in the sales data. This implies that neither seasonal factors nor previous sales play a notable role in determining current sales levels.

4.6 Cross-dependencies between the examined products - MLR model M_2

When similar or closely related products share the same market, especially if they have few distinct features from the consumer’s perspective, it’s common for their demand patterns to influence each other. Identifying these interconnected demand relationships is crucial. By understanding such cross-dependencies, managers can make more accurate predictions, particularly regarding the company’s inventory needs. This foresight aids in refining inventory management, production scheduling, S&OP processes and overall supply chain efficiency. Analyzing these cross-product influences enables better alignment with market demand, supporting more strategic decision-making and enhancing overall business performance.

To extend the previous M_1 regression model (as outlined in equation 4.4.1) for each product, this study introduces the natural logarithms of the sales data from other products into the analysis. To avoid unnecessary model complexity, variables found to be statistically insignificant in the earlier analysis (Chapter 4.5) will be excluded. The refined regression model, M_2 , will only include variables that provide meaningful explanatory power. The adjusted MLR model M_2 , which will be applied to the entire dataset (spanning 48 observations), can be expressed in general terms by the following equation:

$$M_2: \log(S_{t,k}) = \beta_{0,k} + \gamma_{0,k}t + \gamma_{1,k}t^2 + \sum_{i=1}^{11} \beta_{i,k}M_{t,i} + \sum_{j=1}^2 \delta_{j,k} \log(S_{t-j,k}) + \sum_{m \neq k} \delta_{0,m} \log(S_{t,m}) + e_{t,k} \quad (4.5.1)$$

where $k = \{1, 2, \dots, 8\}$ indicates the examined product, $\beta_{0,k}$ is the constant term (intercept) of the time series corresponding to effect of the baseline month December, $\gamma_{0,k}$ and $\gamma_{1,k}$ are the slope coefficients of the linear and quadratic trend respectively, $\beta_{i,k}$ is the coefficient of each monthly dummy variable $M_{t,i}$ where $i = \{1, 2, \dots, 11\}$, $\delta_{j,k}$ is the coefficient of each lag variable $S_{t-j,k}$ where $j = \{1, 2\}$, $\delta_{0,m}$ is the coefficient of the logarithmic sales time series variable $S_{t,m}$ for the different products where $m = \{1, 2, \dots, k - 1\}$, and $e_{t,k}$ is the disturbance or error term.

Following the analysis and discussion in Chapter 4.5 on the use of the M_1 regression model, the statistical significance of each product's sales coefficient ($\delta_{0,m}$) will be assessed using a two-tailed t-test. In this context, the null hypothesis ($H_0: \delta_{0,m} = 0$) implies that the coefficient has no significant effect, while the alternative hypothesis ($H_1: \delta_{0,m} \neq 0$) suggests it does have an impact. Consistent with the previous product evaluations, the significance of the p-values obtained from the regression output will be analyzed at a 95% confidence level.

4.6.1 Interdependencies of product **Ale** with **IPA**, **Lager**, **Pilsner**, **Porter**, **Sour**, **Stout**, **Wheat Beer**

Starting with product **Ale**, the regression summary output for the application of the M_2 model to the sales time series is displayed in **Table 14** below.

Term	Coefficients	Standard Error	T Stat	P-Value
Intercept	14.3347	5.3603	2.6742	0.0109
Lag Variable t-2	-0.4067	0.1397	-2.9117	0.0059
log(S _{IPA})	0.0525	0.1200	0.4374	0.6642
log(S _{Lager})	-0.0842	0.1544	-0.5457	0.5884
log(S _{Pilsner})	0.2475	0.1436	1.7235	0.0927
log(S _{Porter})	-0.0486	0.1502	-0.3235	0.7481
log(S _{Sour})	0.2605	0.1411	1.8459	0.0725
log(S _{Stout})	0.0991	0.1425	0.6950	0.4912
log(S _{Wheat Beer})	-0.0463	0.1310	-0.3537	0.7255

Table 14 “Summary output of model M_2 investigating cross-dependencies between product **Ale** and the remaining seven products”

The results from applying the M_2 model to the sales data of product **Ale**, along with the notably high p-values for the coefficients of the other products, suggest there is no evidence of interdependence between product **Ale** and the rest of the products when evaluated at the 95% confidence level. However, for products **Pilsner** and **Sour**, it's worth noting that while

a cross-dependency does not appear significant at the 5% level, there is evidence of a potential relationship at the 10% significance level between product **Pilsner**'s sales and those of product **Ale** as well as between product **Sour**'s sales and those of product **Ale**.

4.6.2 Interdependencies of product **IPA** with **Ale**, **Lager**, **Pilsner**, **Porter**, **Sour**, **Stout**, **Wheat Beer**

The analysis of potential cross-dependencies in sales continues by investigating possible correlations between product **IPA** and the other products. The summary results from applying the M_2 regression model, using the sales data of **IPA** as the dependent variable and the sales figures of other products as independent variables, are presented in **Table 15**.

Term	Coefficients	Standard Error	T Stat	P-Value
Intercept	15.2030	5.9916	2.5374	0.0153
Lag Variable t-1	-0.5331	0.1467	-3.6349	0.0008
log(S_{Ale})	0.1541	0.1675	0.9203	0.3631
log(S_{Lager})	0.3337	0.1786	1.8680	0.0693
log($S_{Pilsner}$)	0.1287	0.1720	0.7479	0.4590
log(S_{Porter})	0.1298	0.1777	0.7306	0.4694
log(S_{Sour})	0.0836	0.1703	0.4910	0.6262
log(S_{Stout})	-0.2438	0.1555	-1.5673	0.1251
log($S_{Wheat Beer}$)	-0.0320	0.1509	-0.2122	0.8330

Table 15 “Summary output of model M_2 investigating cross-dependencies between product IPA and the remaining seven products”

Evaluating the summary results from the previous table, it becomes clear that the sales of product **IPA** show no significant cross-dependencies with the sales of other products. This conclusion is based on the high p-values of the coefficients, suggesting insufficient evidence to reject the null hypothesis. However, it is worth mentioning that for product **Lager**, while a cross-dependency is not evident at the 5% significance level, there is an indication of a relationship at the 10% level with the sales of product **IPA**.

4.6.3 Interdependencies of product **Lager** with **Ale**, **IPA**, **Pilsner**, **Porter**, **Sour**, **Stout**, **Wheat Beer**

The analysis continues by investigating possible cross-dependencies between the sales of product **Lager** and the other products. **Table 16** presents the results obtained from applying the M_2 regression model, summarizing the relationships between the sales figures of **Lager** and those of the remaining products.

Term	Coefficients	Standard Error	T Stat	P-Value
Intercept	31.3980	6.5075	4.8249	0.0000
M_{t7}	0.1369	0.0781	1.7539	0.0880
M_{t8}	0.1705	0.0771	2.2101	0.0335
Lag Variable t-1	-0.5616	0.1558	-3.6045	0.0009
Lag Variable t-2	-0.3240	0.1465	-2.2110	0.0335
$\log(S_{Ale})$	-0.1140	0.1322	-0.8622	0.3943
$\log(S_{IPA})$	0.0410	0.1130	0.3629	0.7188
$\log(S_{Pilsner})$	0.1342	0.1351	0.9927	0.3275
$\log(S_{Porter})$	-0.0063	0.1385	-0.0456	0.9939
$\log(S_{Sour})$	-0.1563	0.1347	-1.1606	0.2535
$\log(S_{Stout})$	-0.0757	0.1304	-0.5803	0.5654
$\log(S_{Wheat Beer})$	0.0360	0.1193	0.3020	0.7644

Table 16 “Summary output of model M_2 investigating cross-dependencies between product Lager and the remaining seven products”

The regression model results reveal that the sales of product **Lager** show no significant cross-dependencies with the sales of other products. This conclusion is supported by the consistently high p-values of the coefficients for the other products, indicating an inability to reject the null hypothesis. Thus, there is insufficient evidence to suggest any interdependence between product **Lager** and the rest of the product portfolio at the 95% confidence level.

4.6.4 Interdependencies of product **Pilsner** with **Ale, IPA, Lager, Porter, Sour, Stout, Wheat Beer**

The next step in the analysis examines possible interrelationships between the sales time series of product **Pilsner** and those of the other products. The findings from the application of model M_2 are summarized in **Table 17**, highlighting the connections (if any) between the sales performance of product **Pilsner** and that of the other items in the portfolio.

Term	Coefficients	Standard Error	T Stat	P-Value
Intercept	8.3690	5.3643	1.5601	0.1266
$\log(S_{Ale})$	0.2586	0.1488	1.7377	0.0900
$\log(S_{IPA})$	0.0362	0.1278	0.2836	0.7782
$\log(S_{Lager})$	0.1801	0.1617	1.1132	0.2723
$\log(S_{Porter})$	-0.1077	0.1589	-0.6781	0.5016
$\log(S_{Sour})$	-0.0728	0.1561	-0.4666	0.6433
$\log(S_{Stout})$	0.1793	0.1406	1.2748	0.2097
$\log(S_{Wheat Beer})$	-0.0146	0.1395	-0.1045	0.9173

Table 17 “Summary output of model M_2 investigating cross-dependencies between product Pilsner and

The observed high p-values associated with the coefficients for products **Ale**, **IPA**, **Lager**, **Porter**, **Sour**, **Stout** and **Wheat Beer** indicate that there is insufficient evidence to reject the null hypothesis. This suggests that there is no significant interdependence detected between the sales of **Pilsner** and these particular products at the 95% confidence level. It is important to note that, although no cross-dependency is evident at the 5% significance level for product **Pilsner**, there are indications of a potential relationship with the sales of product **Ale** at the 10% significance level.

4.6.5 Interdependencies of product **Porter** with **Ale**, **IPA**, **Lager**, **Pilsner**, **Sour**, **Stout**, **Wheat Beer**

The same analytical approach was applied to examine potential interrelations between the sales of product **Porter** and the sales of the other products. The key findings from the application of model M_2 are compiled in **Table 18**, providing insights into any possible interconnected sales patterns.

Term	Coefficients	Standard Error	T Stat	P-Value
Intercept	13.3502	4.6420	2.8760	0.0066
Linear Trend	0.0177	0.0065	2.7293	0.0096
Quadratic Trend	-0.0004	0.0001	-2.7801	0.0084
log(S_{Ale})	-0.0328	0.1472	-0.2227	0.8250
log(S_{IPA})	-0.0596	0.1195	-0.4989	0.6207
log(S_{Lager})	-0.0135	0.1526	-0.0884	0.9300
log($S_{Pilsner}$)	-0.1206	0.1475	-0.8172	0.4189
log(S_{Sour})	0.0942	0.1493	0.6313	0.5316
log(S_{Stout})	0.1077	0.1322	0.8149	0.4202
log($S_{Wheat Beer}$)	0.1520	0.1306	1.1637	0.2518

Table 18 “Summary output of model M_2 investigating cross-dependencies between product Porter and the remaining seven products”

Reviewing the summary results shown in the preceding table, it is clear that product **Porter** does not demonstrate any interdependence with the sales of the other products. This conclusion is supported by the consistently high p-values of the coefficients, which suggest insufficient evidence to reject the null hypothesis of no cross-dependency.

4.6.6 Interdependencies of product **Sour** with **Ale**, **IPA**, **Lager**, **Pilsner**, **Porter**, **Stout**, **Wheat Beer**

The exploration of potential interconnections between product **Sour** and the sales figures of

other products is the next step in this analysis. **Table 19** provides a summary of the findings based on the application of the M_2 regression model, highlighting the relationships between product **Sour** and the remaining product sales.

Term	Coefficients	Standard Error	T Stat	P-Value
Intercept	7.8476	5.5110	1.4240	0.1624
M_{t8}	-0.0438	0.0889	-0.4926	0.6251
$\log(S_{Ale})$	0.3126	0.1493	2.0938	0.0428
$\log(S_{IPA})$	0.1429	0.1287	1.1101	0.2738
$\log(S_{Lager})$	-0.2125	0.1660	-1.2800	0.2081
$\log(S_{Pilsner})$	-0.0642	0.1621	-0.3960	0.6943
$\log(S_{Porter})$	0.0237	0.1655	0.1429	0.8871
$\log(S_{Stout})$	0.2616	0.1404	1.8635	0.0699
$\log(S_{Wheat Beer})$	0.0285	0.1424	0.2000	0.8426

Table 19 “Summary output of model M_2 investigating cross-dependencies between product Sour and the remaining seven products”

The analysis of **Table 19** predominantly reveals an absence of significant cross-dependencies between the sales of **Sour** and most other products. However, an exception is evident with **Ale**, where the low p-value for its sales coefficient suggests a positive impact on **Sour** sales. This indicates that an increase in the sales of **Ale** could lead to a 31.26% rise in **Sour** sales, assuming other factors remain constant. This finding hints at a linkage in their demand patterns. Such a relationship warrants attention from company managers when making strategic decisions, as it may influence broader sales performance. Additionally, although not significant at the 5% confidence level, potential cross-dependency with **Stout** may be evident at the 10% level, suggesting some degree of interaction worth considering.

4.6.7 Interdependencies of product **Stout** with **Ale**, **IPA**, **Lager**, **Pilsner**, **Porter**, **Sour**, **Wheat Beer**

A similar approach was applied to examine potential interrelationships between the sales of product **Stout** and the sales patterns of the other products. The consolidated results from the implementation of model M_2 are displayed in **Table 20**.

Term	Coefficients	Standard Error	T Stat	P-Value
Intercept	7.2388	5.9806	1.2104	0.2332
$\log(S_{Ale})$	-0.0414	0.1700	-0.2434	0.8089
$\log(S_{IPA})$	-0.1245	0.1396	-0.8914	0.3781
$\log(S_{Lager})$	0.0789	0.1806	0.4372	0.6643
$\log(S_{Pilsner})$	0.2178	0.1708	1.2748	0.2097
$\log(S_{Porter})$	0.1371	0.1748	0.7845	0.4374

$\log(S_{\text{Sour}})$	0.3089	0.1654	1.8675	0.0692
$\log(S_{\text{Wheat Beer}})$	-0.0416	0.1537	-0.2707	0.7880

Table 20 “Summary output of model M_2 investigating cross-dependencies between product Stout and the remaining seven products”

The p-values derived from applying the M_2 regression model to the sales data of **Stout** indicate that the coefficients related to the other products do not show statistical significance, as they exceed the threshold of $\alpha = 0.05$. However, it is noteworthy that for product **Sour**, while the relationship is not significant at the 5% level, evidence of cross-dependence does appear when considering a 10% significance level, suggesting a potential link between the sales of **Sour** and **Stout** at a slightly more lenient confidence threshold.

4.6.8 Interdependencies of product **Wheat Beer** with **Ale, IPA, Lager, Pilsner, Porter, Sour, Stout**

The final product to be analyzed for potential sales cross-dependencies with other products is **Wheat Beer**. The summarized results, obtained from applying the M_2 regression model to the sales data of **Wheat Beer**, are presented in **Table 21**. This analysis includes the natural logarithms of the sales from the other products as explanatory variables.

Term	Coefficients	Standard Error	T Stat	P-Value
Intercept	13.9110	5.8600	2.3739	0.0225
$\log(S_{\text{Ale}})$	-0.0657	0.1745	-0.3765	0.7086
$\log(S_{\text{IPA}})$	-0.0227	0.1449	-0.1568	0.8762
$\log(S_{\text{Lager}})$	0.1077	0.1853	0.5811	0.5644
$\log(S_{\text{Pilsner}})$	-0.0187	0.1791	-0.1045	0.9173
$\log(S_{\text{Porter}})$	0.1141	0.1801	0.6336	0.5299
$\log(S_{\text{Sour}})$	0.0330	0.1772	0.1861	0.8533
$\log(S_{\text{Stout}})$	-0.0440	0.1624	-0.2707	0.7880

Table 21 “Summary output of model M_2 investigating cross-dependencies between product Wheat Beer and the remaining seven products”

The results from the regression model indicate that the sales of product **Wheat Beer** do not exhibit significant cross-dependencies with the sales of other products. This conclusion is reinforced by the consistently high p-values for the coefficients of the other products, which fail to provide enough evidence to reject the null hypothesis. Consequently, at a 95% confidence level, there is no substantial proof of interdependence between product **Wheat Beer** and the other products in the portfolio.

4.7 The effect of the Covid-19 pandemic - MLR model M_3

The Covid-19 pandemic had a significant impact on the resilience and efficiency of global supply chains, emphasizing the vital need for uninterrupted product flow and sustainable operations across all stakeholders. The crisis exposed the far-reaching effects of supply chain disruptions at multiple levels, from suppliers to end consumers, disrupting the performance of industries across various sectors.

Declared a pandemic by the World Health Organization (WHO) in March 2020, the rapid spread of the coronavirus presented numerous challenges for global economies and industries, including the craft beer market. These disruptions highlighted the importance of careful planning and informed decision-making to address both immediate and long-term challenges effectively (Cabras et al., 2023).

This research aims to explore the potential impact of the pandemic on consumer behavior within the craft beer market. To investigate possible shifts in sales trends, a new regression model will be constructed, defining the pandemic period as the timeframe from the implementation of the first Covid-19 measures by the Greek government to their full repeal. The analysis encompasses 48 observations, including the period from the initial lockdown in March 2020 until all restrictions were lifted in April 2022 (Wikipedia, 2024).

To capture this effect, a dummy variable, denoted as $Covid_t$, will be introduced. This variable is assigned a value of 0 for months outside the pandemic period and 1 for months within it, starting from March 2020 through April 2022. The revised regression model M_3 will then be established, incorporating only those explanatory variables that demonstrated statistical significance in the prior analyses for each product.

The following equation presents the revised MLR model M_3 , which incorporates the newly added dummy variable discussed earlier. This model serves as an extension of the previous MLR model M_3 outlined in equation (4.5.1).

$$M_3: \log(S_{t,k}) = \beta_{0,k} + \gamma_{0,k}t + \gamma_{1,k}t^2 + \sum_{i=1}^{11} \beta_{i,k}M_{t,i} + \sum_{j=1}^2 \delta_{j,k} \log(S_{t-j,k}) + \sum_{j \neq k} \delta_{0,m} \log(S_{t,m}) + \beta_c Covid_t + e_{t,k} \quad (4.7.1)$$

where $k = \{1, 2, \dots, 8\}$ indicates the examined product, $\beta_{0,k}$ is the constant term (intercept) of the time series corresponding to effect of the baseline month December, $\gamma_{0,k}$ and $\gamma_{1,k}$ are the slope coefficients of the linear and quadratic trend respectively, $\beta_{i,k}$ is the coefficient of each monthly dummy variable $M_{t,i}$ where $i = \{1, 2, \dots, 11\}$, $\delta_{j,k}$ is the coefficient of each lag

variable $S_{t-j,k}$ where $j=\{1,2\}$, $\delta_{0,m}$ is the coefficient of the logarithmic sales time series variable S_{tmj} for the different products where $m=\{1,2, \dots, k-1\}$, β_c is the coefficient of the dummy variable $Covid_t$ and $e_{t,k}$ is the disturbance or error term.

The following analysis will adopt a similar approach to previous chapters, concentrating on evaluating the significance of the pandemic coefficient (β_c) for each product k . A two-tailed t -distribution will be used for this assessment. The null hypothesis ($H_0: \beta_c = 0$) suggests that the coefficient is not significant, whereas the alternative hypothesis ($H_1: \beta_c \neq 0$) suggests that it is. As in prior analyses, p-values from the regression summary output will be examined at a 95% confidence level to determine statistical significance.

4.7.1 Covid-19 impact on sales of product **Ale**

Starting with product **Ale**, **Table 22** displays the summarized results obtained from applying the M_3 regression model to analyze its sales time series.

Term	Coefficients	Standard Error	T Stat	P-Value
Intercept	21.7736	2.1453	10.1492	0.0000
Lag Variable t-2	-0.4071	0.1388	-2.9340	0.0053
Covid _t	0.0143	0.0457	0.3132	0.7555

Table 22 “Summary output of M_3 model investigating possible impact of Covid-19 pandemic on product Ale”

The results derived from applying the M_3 model to the sales data of product **Ale** indicate that the pandemic period had no statistically significant impact on its sales. This conclusion is based on the pandemic variable’s coefficient, which shows a p-value well above the 0.05 threshold for significance at the 95% confidence level.

4.7.2 Covid-19 impact on sales of product **IPA**

The next product analyzed is **IPA**. **Table 23** provides the results obtained from applying the M_3 regression model to its sales dataset.

Term	Coefficients	Standard Error	T Stat	P-Value
Intercept	22.4744	2.0558	10.9323	0.0000
Lag Variable t-1	-0.4518	0.1327	-3.4041	0.0014
Covid _t	0.0822	0.0491	1.6734	0.1012

Table 23 “Summary output of M_3 model investigating possible impact of Covid-19 pandemic on product IPA”

The Covid-19 variable’s coefficient shows a p-value exceeding the threshold for statistical

significance. This suggests that, at a 95% confidence level, there is no sufficient basis to dismiss the null hypothesis ($H_0: \beta_c = 0$), confirming the insignificance of this coefficient. Therefore, it can be inferred that the pandemic period had no measurable impact on the sales of **IPA**. This conclusion is further supported by **Figure 6**, which shows no distinct deviation or trend in IPA sales during the pandemic period compared to the pre-pandemic period.

4.7.3 Covid-19 impact on sales of product **Lager**

The analysis proceeds with evaluating the potential effects of the pandemic period on the sales of product **Lager**. The findings obtained from the implementation of the M_3 regression model are summarized in **Table 24**.

Term	Coefficients	Standard Error	T Stat	P-Value
Intercept	27.4417	3.7569	7.3044	0.0000
M_{t8}	0.1720	0.0730	2.3571	0.0230
Lag Variable t-1	-0.4974	0.1433	-3.4705	0.0012
Lag Variable t-2	-0.2740	0.1459	-1.8783	0.0671
$Covid_t$	0.0250	0.0394	0.6354	0.5285

Table 24 “Summary output of M_3 model investigating possible impact of Covid-19 pandemic on product Lager”

The results from the M_3 regression model reveal that the p-value linked to the coefficient of the pandemic dummy variable is greater than the threshold of $\alpha = 0.05$. Therefore, the null hypothesis remains accepted, indicating a lack of statistical support for the notion that the pandemic period significantly affected this product’s sales within the 95% confidence interval.

4.7.4 Covid-19 impact on sales of product **Pilsner**

The same analysis proceeds with product **Pilsner**, with the regression results from applying the M_3 model presented in **Table 25**. These outcomes reflect the impact of the model on the product’s sales data.

Term	Coefficients	Standard Error	T Stat	P-Value
Intercept	15.5172	0.0337	460.8191	0.0000
$Covid_t$	-0.0533	0.0458	-1.1644	0.2503

Table 25 “Summary output of M_3 model investigating possible impact of Covid-19 pandemic on product Pilsner”

Similar to the analysis of earlier products, the high p-value linked to the coefficient of the Covid-19 dummy variable indicates that there is no significant evidence to suggest the

pandemic period had an impact on the product's sales.

4.7.5 Covid-19 impact on sales of product **Porter**

The analysis moves forward by investigating the potential impact of the Covid-19 period on the sales of product **Porter**. The results from applying regression model M_3 to this product's sales data are shown in **Table 26**.

Term	Coefficients	Standard Error	T Stat	P-Value
Intercept	15.3074	0.0813	188.2159	0.0000
Linear Trend	0.0145	0.0062	2.3315	0.0244
Quadratic Trend	-0.0003	0.0001	-1.9224	0.0610
Covid _t	0.0462	0.0665	0.6948	0.4908

Table 26 “Summary output of M_3 model investigating possible impact of Covid-19 pandemic on product Porter”

The analysis of product **Porter**'s sales data using the M_3 model reveals that the pandemic period did not have a significant effect on its sales. This is evident from the coefficient of the pandemic variable, which has a p-value significantly higher than the 0.05 threshold, indicating no statistical significance at the 95% confidence level.

4.7.6 Covid-19 impact on sales of product **Sour**

The next product analyzed for potential sales changes during the pandemic period is **Sour**. The summary results from applying the MLR model M_3 to its sales data are presented in **Table 27**.

Term	Coefficients	Standard Error	T Stat	P-Value
Intercept	10.1750	2.1632	4.7037	0.0000
log(S _{Ale})	0.3445	0.1397	2.4653	0.0176
Covid _t	-0.0511	0.0464	-1.1019	0.2764

Table 27 “Summary output of M_3 model investigating possible impact of Covid-19 pandemic on product Sour”

The coefficient for the Covid-19 variable yields a p-value that surpasses the critical threshold for statistical significance. This indicates that, at a 95% confidence level, there is not enough evidence to reject the null hypothesis ($H_0: \beta_c = 0$), supporting the conclusion that the pandemic did not have a significant effect on the sales of **Sour**.

4.7.7 Covid-19 impact on sales of product **Stout**

The next phase of the analysis examines the possible impact of the pandemic on the sales of

product **Stout**. The results from applying the M_3 regression model are presented in **Table 28**.

Term	Coefficients	Standard Error	T Stat	P-Value
Intercept	15.5523	0.0369	421.4014	0.0000
Covid _t	-0.0520	0.0501	-1.0362	0.3055

Table 28 “Summary output of M_3 model investigating possible impact of Covid-19 pandemic on product Stout”

The application of the M_3 model to the sales data of product **Stout** reveals that the pandemic period did not significantly affect its sales. This conclusion stems from the high p-value associated with the pandemic variable’s coefficient, which exceeds the 0.05 significance threshold at the 95% confidence level.

4.7.8 Covid-19 impact on sales of product **Wheat Beer**

The last product examined for the possible effects of the Covid-19 pandemic on its sales is product **Wheat Beer**. The results from applying the M_3 model to its sales data are presented in **Table 29**.

Term	Coefficients	Standard Error	T Stat	P-Value
Intercept	15.5427	0.0357	435.8880	0.0000
Covid _t	-0.0487	0.0484	-1.0060	0.3197

Table 29 “Summary output of M_3 model investigating possible impact of Covid-19 pandemic on product Wheat Beer”

As with the previous products, the elevated p-value associated with the coefficient of the Covid-19 dummy variable suggests that there is no significant evidence to support the idea that the pandemic period affected the product’s sales.

4.8 Development and Implementation of Sales Forecasting Models

As detailed in Chapter 3.1, this dissertation adopts a methodology that leverages multiple MLR models (M_1 , M_2 , M_3) to analyze the statistical characteristics of the selected products and explore their sales trends. In the following sections, the initial MLR model, M_1 , will be repurposed as a forecasting framework to estimate future demand. The forecasting models will incorporate only those explanatory variables deemed statistically significant based on p-values calculated using Excel’s regression tools, as evaluated in earlier analyses. However, lag variables will be included in the models regardless of their statistical significance. This inclusion ensures a deeper understanding of the relationships between variables and provides insight into how historical data influences current outcomes.

The following sections will detail the regression models employed for estimating each product's sales, focusing on a sample of 36 observations from the total dataset (covering the period from January 2020 to December 2022). The output summaries generated using Excel's linear regression tool will be provided, alongside the finalized structure of the forecasting MLR M_1 model. Once established, the M_1 model will be applied to a separate dataset of 12 observations representing the forecasting period from January 2023 to December 2023. This approach will enable an evaluation of the model's forecasting accuracy, utilizing metrics such as MAE and MAPE.

The second forecasting approach to be utilized is the EWMA model, previously explained in Chapter 3.2. Using equation (3.2.1), the model will be applied to the estimation dataset, after which the MAE and MAPE will be calculated. To refine the model, Excel's Solver tool will be employed to determine the optimal λ parameter value, aiming to minimize the MAPE within the estimation dataset and improve the model's forecasting accuracy. To support the analysis, graphical representations will be created to illustrate the forecast outcomes and the errors associated with the models, offering a clearer understanding of their accuracy and effectiveness. Finally, a comparative analysis of the MAE and MAPE values obtained from the forecasting dataset for both models will be carried out, providing insights and drawing key conclusions.

4.8.1 Forecasting MLR model M_1 of product Ale

Table 30 displays the summarized results from applying the M_1 regression model to the *estimation sample* of the product's sales data. These findings allow the researcher to identify the structure of the forecasting model that will be utilized to generate sales projections.

Term	Coefficients	Standard Error	T Stat	P-Value
Intercept	26.8940	4.3449	6.1898	0.0000
Linear Trend	-0.0050	0.0103	-0.4884	0.6305
Quadratic Trend	0.0000	0.0003	-0.0669	0.9473
M_{t1}	0.0668	0.1343	0.4972	0.6245
M_{t2}	-0.1112	0.1303	-0.8535	0.4035
M_{t3}	-0.2040	0.1356	-1.5046	0.1480
M_{t4}	-0.0899	0.1381	-0.6508	0.5226
M_{t5}	0.0030	0.1296	0.0229	0.9820
M_{t6}	-0.0548	0.1309	-0.4188	0.6799
M_{t7}	0.0962	0.1374	0.7006	0.4916
M_{t8}	-0.0587	0.1275	-0.4609	0.6499
M_{t9}	-0.1055	0.1310	-0.8055	0.4300

M_{t10}	-0.1605	0.1318	-1.2175	0.2376
M_{t11}	-0.0449	0.1308	-0.3430	0.7352
Lag Variable t-1	-0.1643	0.1900	-0.8646	0.3975
Lag Variable t-2	-0.5630	0.1895	-2.9700	0.0076

Table 30 “Summary output of M_1 model implemented in product Ale”

The equation presented below represents the MLR model that will be applied to the forecasting sample for the product.

$$M_1: \log(\widehat{S}_{t,1}) = 26.8940 - 0.1643 \log(S_{t-1,1}) - 0.5630 \log(S_{t-2,1}) \quad (4.8.1.1)$$

It is important to note that the sales data underwent a natural logarithmic transformation. Therefore, to implement the specified model and draw meaningful conclusions, the Excel function EXP(.) must be utilized to reverse the initial LN(.) transformation.

Figure 27 illustrates a comparison between the forecasted sales and the actual sales during the evaluation period, following the implementation of model M_1 on the out-of-sample data set (referencing regression equation 4.8.1.1).

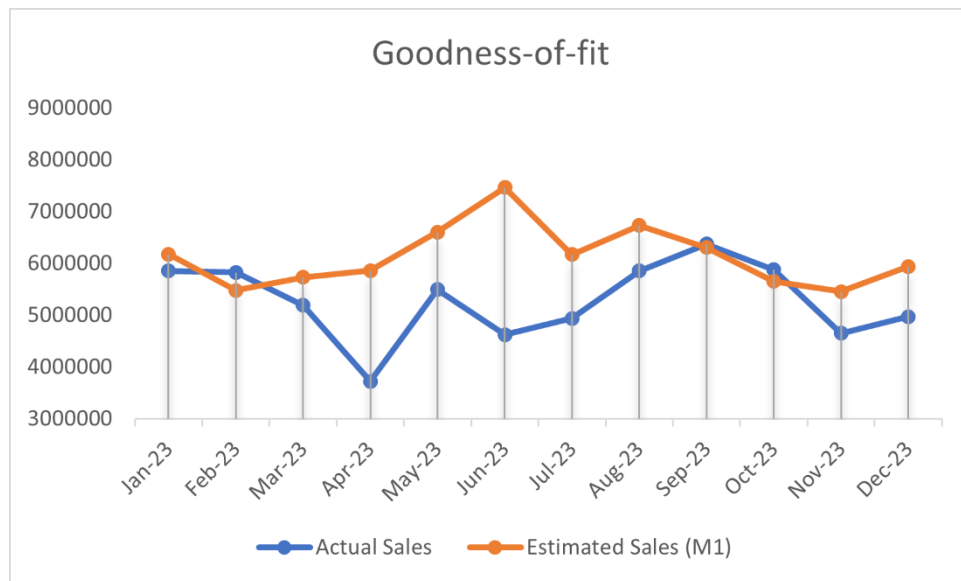


Figure 27, “Time series plot of forecasted Ale sales”

In addition, **Figure 28** displays the time series plot of the residuals from the implemented M_1 regression model, aiming to identify any potential patterns or anomalies in the forecasting errors.

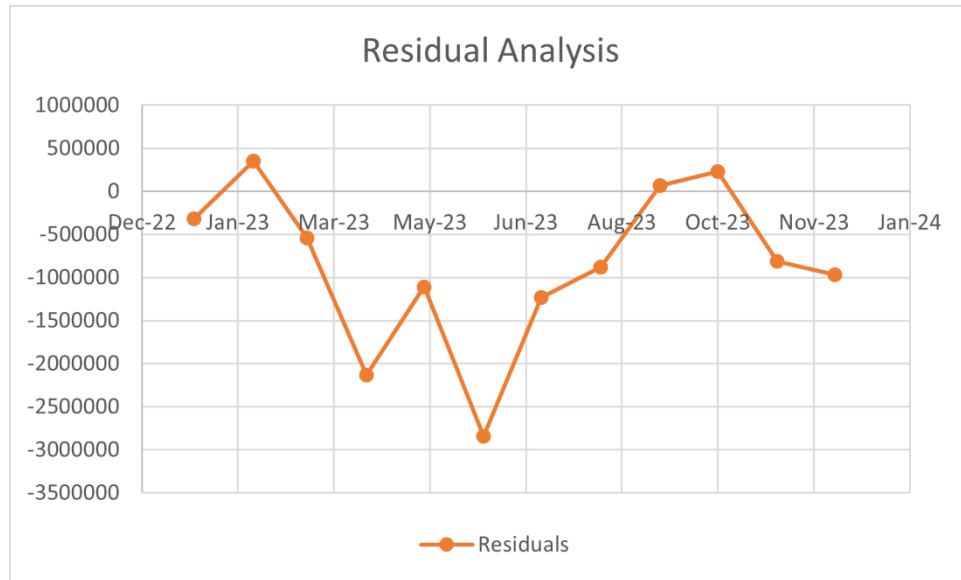


Figure 28, “Residual Analysis of product Ale”

Figure 27 indicates that the model demonstrates some ability to capture the overall trend in actual sales. However, it frequently overestimates the actual sales values, leading to a lack of alignment in certain periods. This observation is reinforced by **Figure 28**, where the residuals predominantly exhibit negative values, confirming the consistent overestimation by the model.

4.8.2 Forecasting MLR model M_1 of product IPA

The following **Table 31** displays the summary results obtained from applying the M_1 regression model to the product’s sales data within the estimation sample.

Term	Coefficients	Standard Error	T Stat	P-Value
Intercept	35.0348	4.9994	7.0078	0.0000
Linear Trend	0.0508	0.0124	4.0905	0.0006
Quadratic Trend	-0.0013	0.0003	-4.1537	0.0005
M_{t1}	0.0696	0.1363	0.5106	0.6152
M_{t2}	-0.0849	0.1374	-0.6178	0.5437
M_{t3}	-0.0300	0.1284	-0.2339	0.8174
M_{t4}	-0.1310	0.1327	-0.9877	0.3351
M_{t5}	0.0090	0.1292	0.0700	0.9449
M_{t6}	-0.1822	0.1297	-1.4053	0.1753
M_{t7}	-0.1332	0.1271	-1.0481	0.3071
M_{t8}	-0.1014	0.1284	-0.7893	0.4392

M_{t9}	-0.1352	0.1280	-1.0559	0.3036
M_{t10}	-0.1106	0.1261	-0.8777	0.3905
M_{t11}	-0.1935	0.1271	-1.5220	0.1437
Lag Variable t-1	-0.7530	0.1890	-3.9841	0.0007
Lag Variable t-2	-0.5216	0.1893	-2.7547	0.0122

Table 31 “Summary output of M_1 model implemented in product IPA”

The following equation represents the MLR model that will be applied to the product’s forecasting sample.

$$M_1: \log(\widehat{S}_{t,2}) = 35.0348 + 0.0508t - 0.0013t^2 - 0.7530 \log(S_{t-1,2}) - 0.5216 \log(S_{t-2,2}) \quad (4.8.2.1)$$

After applying the regression model (equation 4.8.2.1) to the product’s forecasting sample, sales predictions were generated. **Figure 29** illustrates the comparison between the predicted sales and the actual sales during the forecast period.

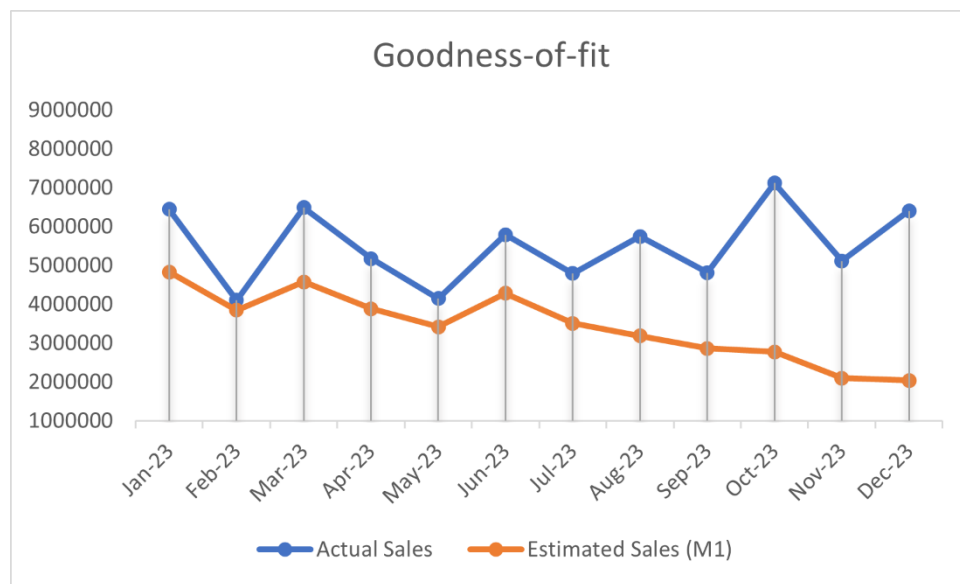


Figure 29, “Time series plot of forecasted IPA sales”

Additionally, **Figure 30** displays the time series of residuals from the M_1 regression model to identify any potential patterns in the errors.

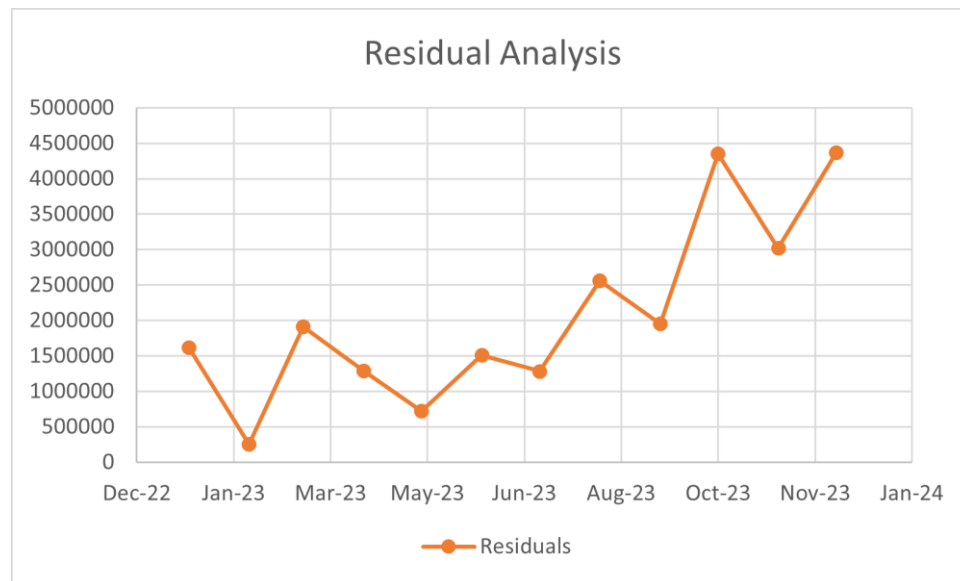


Figure 30, “Residual Analysis of product IPA”

Figure 29 shows that the model captures the general sales trend to some extent but consistently falls short of accurately predicting actual sales, resulting in noticeable discrepancies during specific periods. This pattern is further supported by **Figure 30**, which highlights that the residuals are exclusively positive, indicating a persistent underprediction of sales throughout the analyzed timeframe.

4.8.3 Forecasting MLR model M_1 of product Lager

Table 32 below shows the summary output from applying the MLR model M_1 to the sales data of the product’s estimation sample. Using the same approach as with the other products, the results from this model will be used to define the appropriate forecasting model.

Term	Coefficients	Standard Error	T Stat	P-Value
Intercept	34.9772	5.2519	6.6600	0.0000
Linear Trend	0.0049	0.0082	0.5996	0.5555
Quadratic Trend	-0.0001	0.0002	-0.5956	0.5581
M_{t1}	0.1722	0.1048	1.6432	0.1160
M_{t2}	0.1452	0.1052	1.3801	0.1828
M_{t3}	0.1709	0.1046	1.6343	0.1178
M_{t4}	0.1107	0.1013	1.0927	0.2875
M_{t5}	0.1541	0.1011	1.5248	0.1430
M_{t6}	0.2273	0.1012	2.2471	0.0361
M_{t7}	0.2633	0.1027	2.5637	0.0185
M_{t8}	0.3741	0.1032	3.6241	0.0017

M_{t9}	0.2266	0.1081	2.0955	0.0491
M_{t10}	0.1722	0.1042	1.6528	0.1140
M_{t11}	0.0898	0.1004	0.8949	0.3815
Lag Variable t-1	-0.7512	0.1933	-3.8858	0.0009
Lag Variable t-2	-0.5168	0.1993	-2.5926	0.0174

Table 32 “Summary output of M_1 model implemented in product Lager”

The equation presented below represents the MLR model that will be applied to the forecasting sample for the product.

$$M_1: \log(\widehat{S}_{t,3}) = 34.9772 + 0.0049t - 0.0001t^2 + 0.2273M_{t6} + 0.2633M_{t7} + 0.3741M_{t8} + 0.2266M_{t9} - 0.7512 \log(S_{t-1,3}) - 0.5168 \log(S_{t-2,3}) \quad (4.8.3.1)$$

Upon applying the regression model (equation 4.8.3.1) to the product’s forecasting sample, sales predictions were obtained. **Figures 31** and **32** present a visual comparison of the predicted versus actual sales and a time series chart of the residuals, respectively. These illustrations provide a detailed view of the model’s predictive accuracy and residual behavior over the evaluation period, aiding in assessing the model’s performance and uncovering any patterns in the errors.

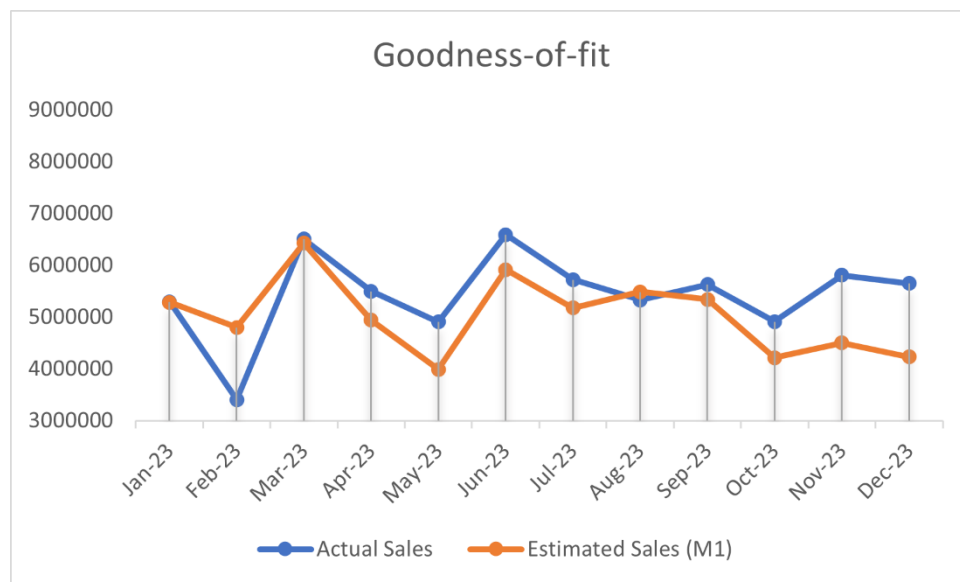


Figure 31, “Time series plot of forecasted Lager sales”

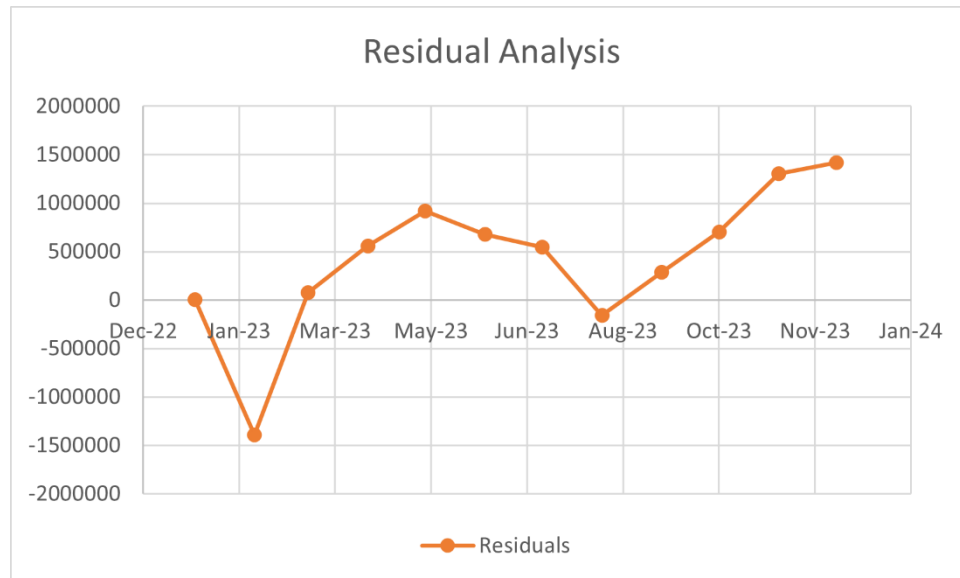


Figure 32, “Residual Analysis of product Lager”

The provided graphs evaluate the effectiveness of the regression model M_1 in predicting actual sales. Based on **Figure 31**, the model M_1 captures the general sales trends, though it frequently underestimates actual sales values. This is evident in the periodic deviations where the estimated sales line is consistently below the actual sales line. **Figure 32** supports this observation. It shows that residuals are predominantly positive, indicating that the model often predicts lower sales than what actually occurs. Despite this, the model still reflects seasonal fluctuations reasonably well, albeit with a bias toward underestimation.

4.8.4 Forecasting MLR model M_1 of product **Pilsner**

Table 33 presents the summary output generated from the application of regression model M_1 to the product’s estimation sample. Consistent with the approach used for previous products, the results of this model will be used to establish the structure of the forecasting model.

Term	Coefficients	Standard Error	T Stat	P-Value
Intercept	22.8565	5.5936	4.0862	0.0006
Linear Trend	-0.0001	0.0117	-0.0104	0.9918
Quadratic Trend	0.0001	0.0003	0.2350	0.8166
M_{t1}	0.0508	0.1517	0.3349	0.7412
M_{t2}	-0.0505	0.1452	-0.3475	0.7318
M_{t3}	0.1359	0.1513	0.8980	0.3798
M_{t4}	0.0839	0.1455	0.5765	0.5707
M_{t5}	0.1199	0.1546	0.7757	0.4470
M_{t6}	0.1637	0.1486	1.1016	0.2837
M_{t7}	0.0744	0.1509	0.4931	0.6273

M_{t8}	0.1749	0.1530	1.1434	0.2664
M_{t9}	0.1490	0.1474	1.0106	0.3243
M_{t10}	-0.0690	0.1552	-0.4445	0.6615
M_{t11}	0.0667	0.1543	0.4322	0.6702
Lag Variable t-1	-0.2813	0.2258	-1.2456	0.2273
Lag Variable t-2	-0.2022	0.2304	-0.8776	0.3906

Table 33 “Summary output of M_1 model implemented in product Pilsner”

The equation presented below represents the MLR model that will be applied to the forecasting sample for the product.

$$M_1: \log(\widehat{S}_{t,4}) = 22.8565 - 0.2813 \log(S_{t-1,4}) - 0.2022 \log(S_{t-2,4}) \quad (4.8.4.1)$$

By applying equation 4.8.4.1 to the product’s forecasting sample, sales projections were obtained. **Figures 33** and **34** display a side-by-side comparison of the forecasted versus actual sales, as well as a time series plot of the residuals. As discussed earlier, these visual aids serve to offer a clear perspective on the model’s predictive accuracy and to highlight any discernible patterns in the residuals throughout the forecasting period.

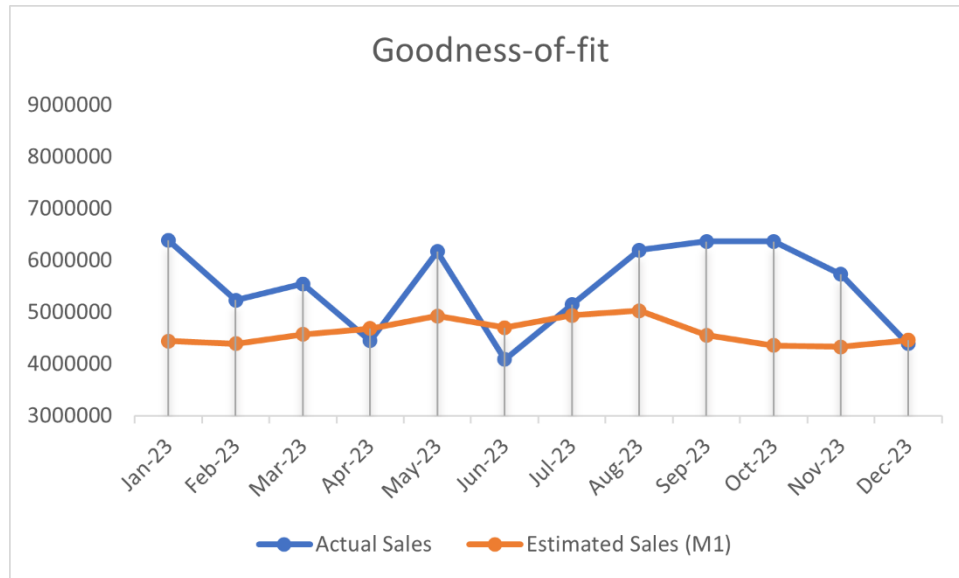


Figure 33, “Time series plot of forecasted Pilsner sales”

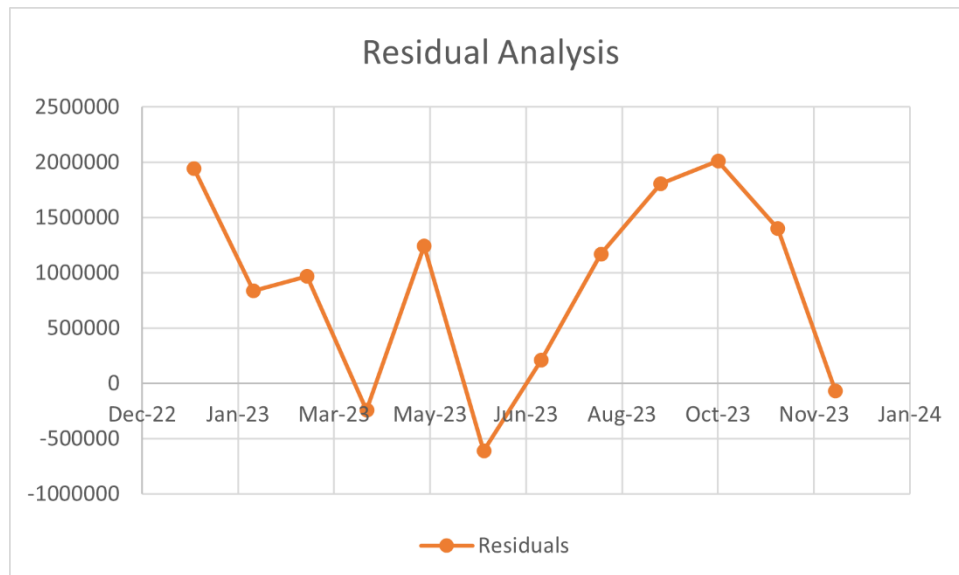


Figure 34, “Residual Analysis of product Pilsner”

The presented graphs reveal that the regression model M_1 does not provide an ideal fit for forecasting actual sales. In **Figure 33**, the estimated sales generally deviate from the actual sales, showing a consistent underestimation of sales figures. This suggests that the model struggles to capture the true variability in sales data. Additionally, **Figure 34** further supports this observation, as the residuals fluctuate without a discernible pattern but remain predominantly positive. This consistent bias in the residuals indicates systematic underprediction by the model, highlighting a need for adjustments or refinements to better align with actual sales trends.

4.8.5 Forecasting MLR model M_1 of product **Porter**

Table 34 displays the summarized output generated from implementing the M_1 regression model on the product's estimation dataset.

Term	Coefficients	Standard Error	T Stat	P-Value
Intercept	16.8540	4.5377	3.7142	0.0014
Linear Trend	0.0093	0.0091	1.0179	0.3209
Quadratic Trend	-0.0001	0.0002	-0.4241	0.6760
M_{t1}	0.0582	0.1154	0.5039	0.6198
M_{t2}	-0.1347	0.1145	-1.1767	0.2531
M_{t3}	0.0027	0.1181	0.0225	0.9823
M_{t4}	-0.2219	0.1116	-1.9880	0.0607
M_{t5}	-0.0461	0.1179	-0.3908	0.7001
M_{t6}	-0.3088	0.1135	-2.7212	0.0132
M_{t7}	-0.1131	0.1229	-0.9209	0.3681
M_{t8}	-0.1918	0.1193	-1.6079	0.1235
M_{t9}	-0.0112	0.1128	-0.0990	0.9221
M_{t10}	-0.1105	0.1110	-0.9956	0.3314
M_{t11}	-0.0282	0.1114	-0.2528	0.8030
Lag Variable t-1	0.1140	0.2209	0.5161	0.6114
Lag Variable t-2	-0.2038	0.2278	-0.8945	0.3817

Table 34 “Summary output of M_1 model implemented in product Porter”

The equation presented below represents the MLR model that will be applied to the forecasting sample for the product.

$$M_1: \log(\widehat{S}_{t,5}) = 16.8540 - 0.3088M_{t6} - 0.1140 \log(S_{t-1,5}) - 0.2038 \log(S_{t-2,5})$$

(4.8.5.1)

Following the application of regression equation 4.8.5.1 to the product's forecasting dataset, sales predictions and corresponding model errors were calculated. These results are illustrated in **Figures 35** and **36**.

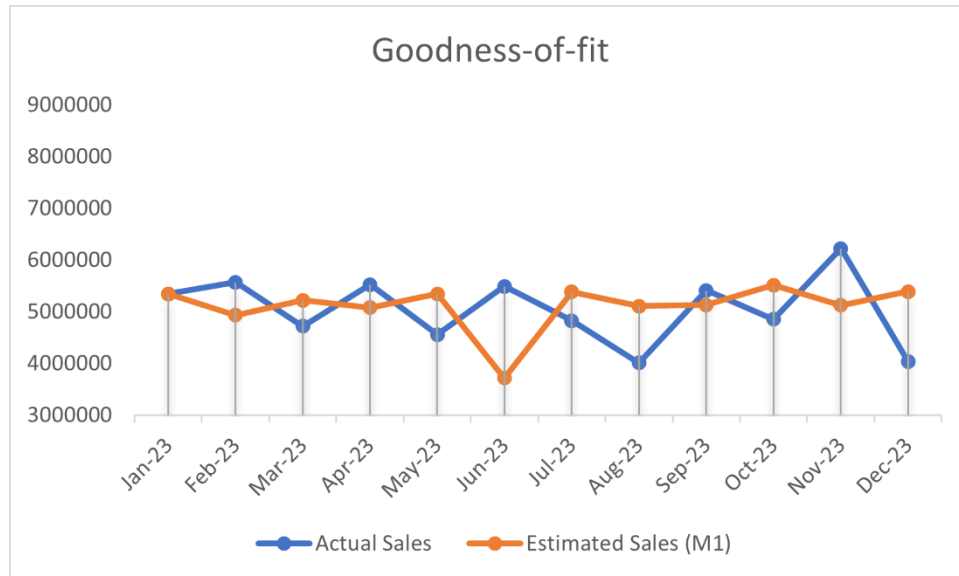


Figure 35, “Time series plot of forecasted Porter sales”

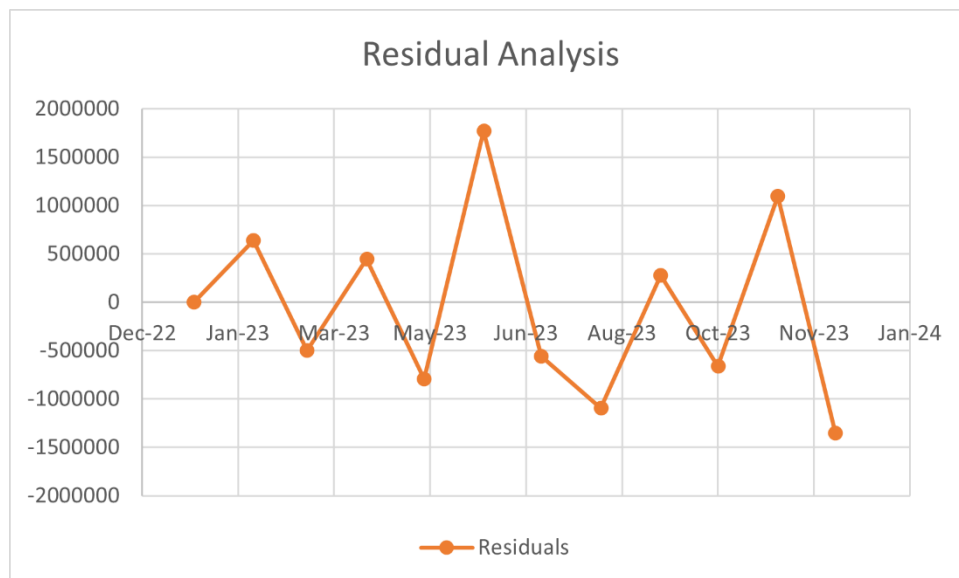


Figure 36, “Residual Analysis of product Porter”

Based on **Figure 35**, the forecasting model M_1 shows a partial alignment with the actual sales data throughout the evaluated period, though some deviations are apparent. In **Figure 36**, the residuals fluctuate around the zero line, indicating that the errors are relatively minor and dispersed without a discernible pattern. This suggests that the model captures a substantial portion of the variability in the data and the residuals are largely random. The absence of a systematic pattern in the residuals implies that key regression assumptions, such as linearity, homoscedasticity (constant variance of errors), and the randomness of residuals, are likely upheld, contributing to the reliability of the model’s predictive performance.

4.8.6 Forecasting MLR model M_1 of product **Sour**

The analysis now turns to product **Sour**. **Table 35** presents the outcomes obtained from applying model M_1 , based on equation 4.8.6.1, to the product's estimation dataset.

Term	Coefficients	Standard Error	T Stat	P-Value
Intercept	21.1660	5.6286	3.7604	0.0012
Linear Trend	-0.0012	0.0116	-0.1046	0.9178
Quadratic Trend	0.0000	0.0003	0.0334	0.9737
M_{t1}	-0.0437	0.1497	-0.2920	0.7733
M_{t2}	-0.2928	0.1528	-1.9160	0.0698
M_{t3}	-0.2628	0.1512	-1.7383	0.0975
M_{t4}	-0.1629	0.1482	-1.0997	0.2845
M_{t5}	-0.0925	0.1444	-0.6404	0.5292
M_{t6}	-0.2080	0.1461	-1.4243	0.1698
M_{t7}	-0.2704	0.1461	-1.8506	0.0791
M_{t8}	-0.2837	0.1451	-1.9551	0.0647
M_{t9}	-0.2479	0.1453	-1.7067	0.1034
M_{t10}	-0.2299	0.1439	-1.5979	0.1258
M_{t11}	-0.1838	0.1431	-1.2844	0.2137
Lag Variable t-1	-0.3145	0.2281	-1.3788	0.1832
Lag Variable t-2	-0.0412	0.2298	-0.1792	0.8596

Table 35 “Summary output of M_1 model implemented in product Sour”

The equation presented below represents the MLR model that will be applied to the forecasting sample for the product.

$$M_1: \log(\widehat{S}_{t,6}) = 21.1660 - 0.3145 \log(S_{t-1,6}) - 0.0412 \log(S_{t-2,6}) \quad (4.8.6.1)$$

The forecasting sample will be analyzed using this equation to produce sales predictions and evaluate the model's accuracy. **Figures 37** and **38** provide a comparison between the projected sales generated by model M_1 and the actual sales figures, along with a visualization of the associated residuals.

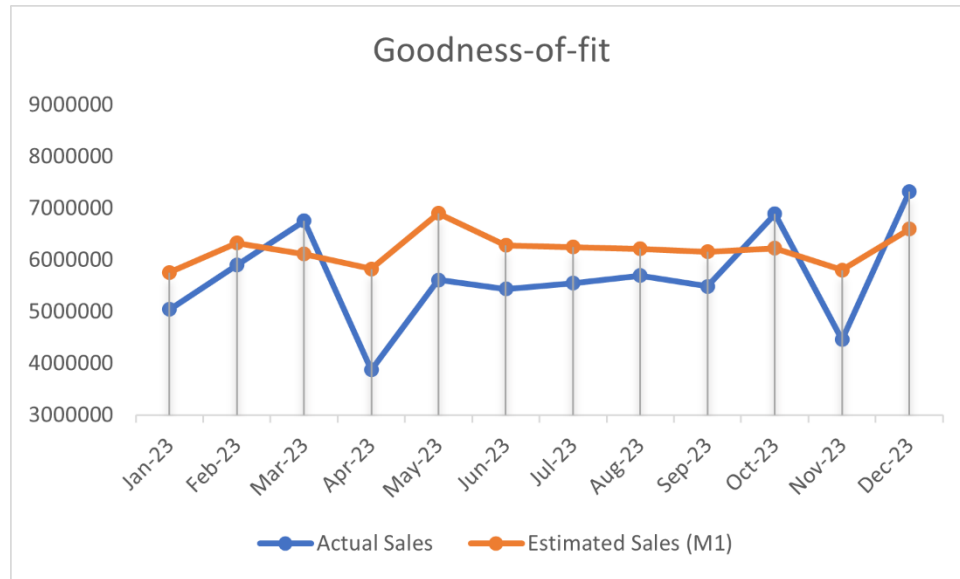


Figure 37, “Time series plot of forecasted Sour sales”

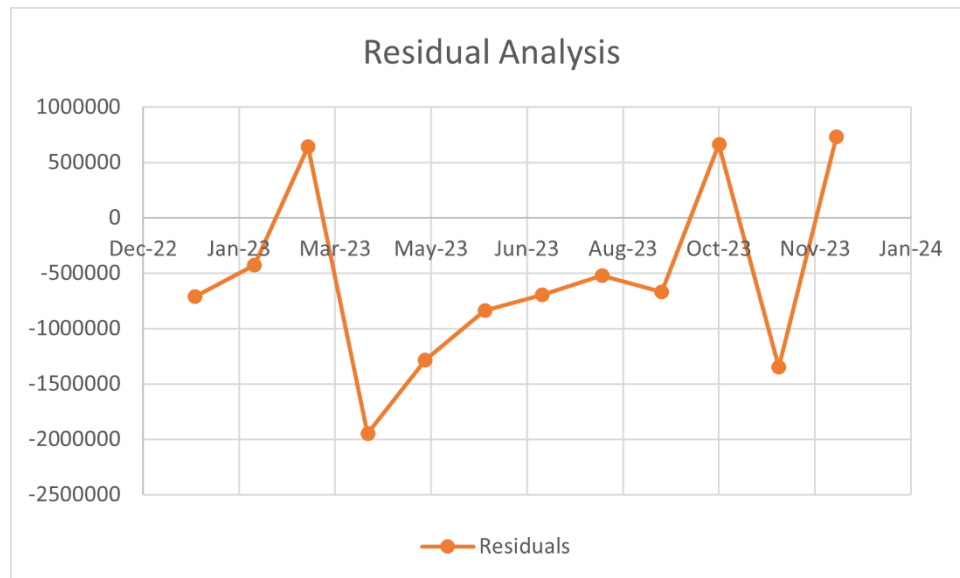


Figure 38, “Residual Analysis of product Sour”

Figure 37 demonstrates that model M_1 somewhat aligns with the actual sales data, capturing the general trend to some extent. However, there are noticeable discrepancies, particularly during periods of pronounced sales peaks where the model underestimates the actual sales and during troughs where the model overestimates. This mismatch is evident from the divergence between the two lines. **Figure 38** reinforces these observations through a residual analysis, which shows significant variability in the residuals, diverging markedly from zero. Both positive and negative deviations indicate the model’s limitations in closely tracking the actual sales behavior. The patterns of variability suggest that the model requires further refinement to better capture the complexities and fluctuations inherent in the sales data.

4.8.7 Forecasting MLR model M_1 of product **Stout**

Table 36 presents the summarized results obtained from applying the M_1 regression model to the product's estimation dataset.

Term	Coefficients	Standard Error	T Stat	P-Value
Intercept	16.5830	4.8778	3.3997	0.0028
Linear Trend	-0.0041	0.0139	-0.2960	0.7703
Quadratic Trend	0.0002	0.0004	0.5157	0.6117
M_{t1}	0.1837	0.1705	1.0776	0.2941
M_{t2}	-0.1373	0.1747	-0.7858	0.4412
M_{t3}	0.1253	0.1725	0.7268	0.4758
M_{t4}	-0.0050	0.1752	-0.0286	0.9775
M_{t5}	0.0481	0.1679	0.2864	0.7775
M_{t6}	-0.0383	0.1675	-0.2289	0.8212
M_{t7}	0.2229	0.1662	1.3409	0.1950
M_{t8}	0.0326	0.1759	0.1855	0.8547
M_{t9}	-0.0929	0.1708	-0.5440	0.5925
M_{t10}	0.0549	0.1661	0.3307	0.7443
M_{t11}	-0.0442	0.1699	-0.2603	0.7973
Lag Variable t-1	0.0148	0.2196	0.0672	0.9741
Lag Variable t-2	-0.0860	0.2253	-0.3819	0.7066

Table 36 “Summary output of M_1 model implemented in product Stout”

The equation presented below represents the MLR model that will be applied to the forecasting sample for the product.

$$M_1: \log(\widehat{S}_{t,7}) = 16.5830 + 0.0148 \log(S_{t-1,7}) - 0.0860 \log(S_{t-2,7}) \quad (4.8.7.1)$$

By using equation 4.8.7.1 on the product's forecasting data, sales estimates were generated. **Figures 39** and **40** show a comparison between the predicted and actual sales, along with a time series plot of the residuals. As mentioned previously, these visual representations help assess the accuracy of the model's forecasts and reveal any patterns in the residuals over the forecasting period.

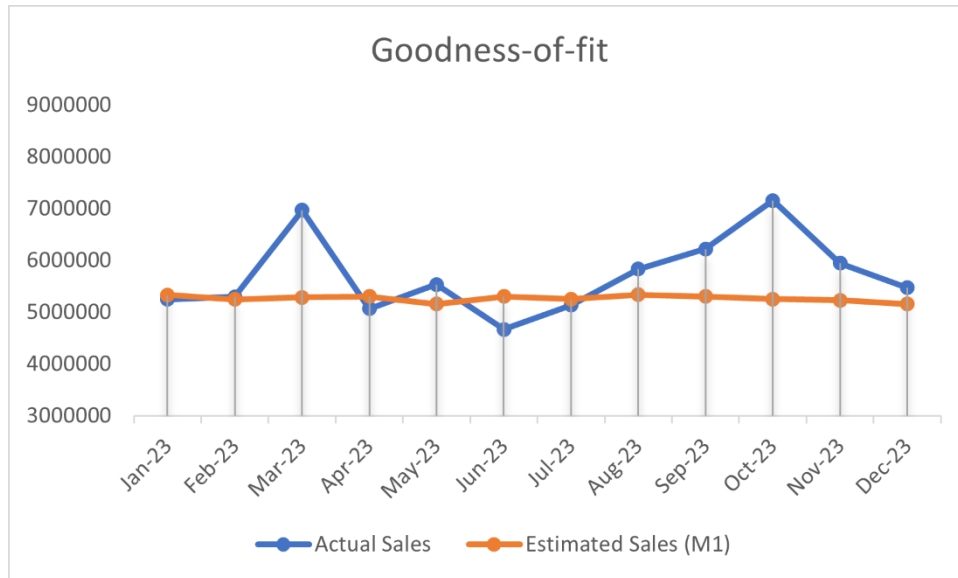


Figure 39, “Time series plot of forecasted Stout sales”

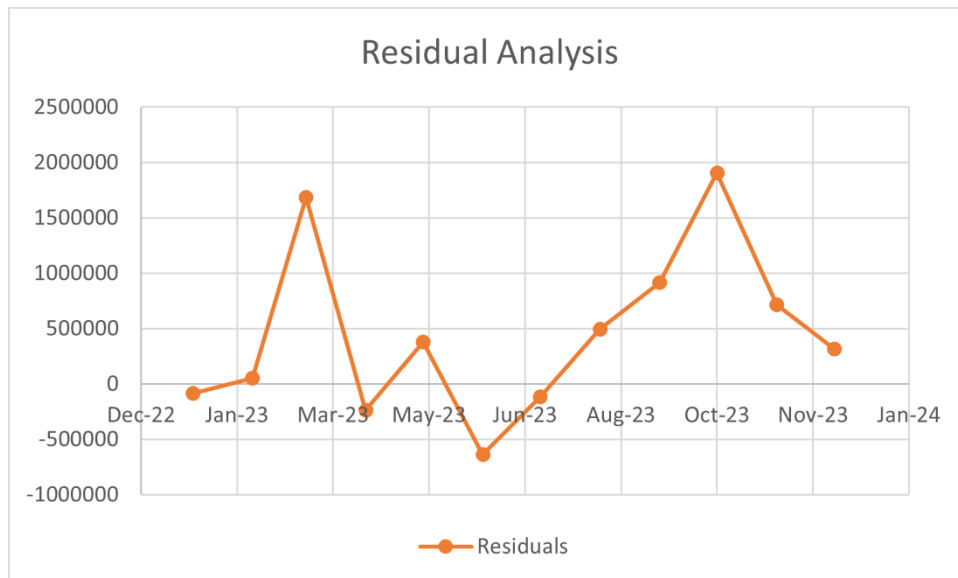


Figure 40, “Residual Analysis of product Stout”

The graphs demonstrate that the M_1 regression model falls short of accurately forecasting actual sales. **Figure 39** highlights a noticeable gap between predicted and actual sales, with the model consistently underestimating sales values, indicating difficulty in capturing the full variability of the data. Moreover, **Figure 40** reinforces this finding, showing residuals that vary erratically but remain mostly positive. This persistent pattern suggests a systematic underforecasting, emphasizing the need for model adjustments or enhancements to improve its alignment with actual sales behavior.

4.8.8 Forecasting MLR model M_1 of product **Wheat Beer**

The final analysis focuses on product **Wheat Beer**, with **Table 37** summarizing the results

from the M_1 model. Following this, the finalized version of the model, intended for use with the product's forecasting sample, will be introduced.

Term	Coefficients	Standard Error	T Stat	P-Value
Intercept	15.2922	4.5604	3.3532	0.0032
Linear Trend	-0.0254	0.0126	-2.0153	0.0575
Quadratic Trend	0.0007	0.0003	2.1415	0.0447
M_{t1}	0.1886	0.1462	1.2905	0.2116
M_{t2}	-0.0657	0.1492	-0.4405	0.6643
M_{t3}	0.1050	0.1393	0.7539	0.4597
M_{t4}	0.1029	0.1448	0.7110	0.4853
M_{t5}	0.0556	0.1403	0.3967	0.6958
M_{t6}	0.0681	0.1380	0.4938	0.6268
M_{t7}	-0.0233	0.1382	-0.1686	0.8678
M_{t8}	0.1884	0.1355	1.3905	0.1796
M_{t9}	-0.0389	0.1470	-0.2644	0.7942
M_{t10}	0.0844	0.1365	0.6179	0.5436
M_{t11}	-0.0394	0.1409	-0.2798	0.7825
Lag Variable t-1	-0.0076	0.2200	-0.0346	0.9727
Lag Variable t-2	0.0284	0.2080	0.1366	0.8927

Table 37 “Summary output of M_1 model implemented in product Wheat Beer”

$$M_1: \log(\widehat{S}_{t,8}) = 15.2922 + 0.0007t^2 - 0.0076 \log(S_{t-1,8}) - 0.0284 \log(S_{t-2,8})$$

(4.8.8.1)

Following the application of the previously mentioned equation to the product's forecasting sample, the outcomes are illustrated in **Figures 41** and **42** through the corresponding graphs. The graphs clearly show that the model consistently overestimates actual sales, as reflected by the predominantly negative residuals throughout the performance period. The downward trend in the errors suggests that the model fails to capture the true dynamics of the sales data. This indicates the need for further analysis to enhance the model's accuracy. Potential improvements could include refining the model structure, examining outliers or influential observations, or incorporating additional explanatory variables to better represent the factors influencing sales.

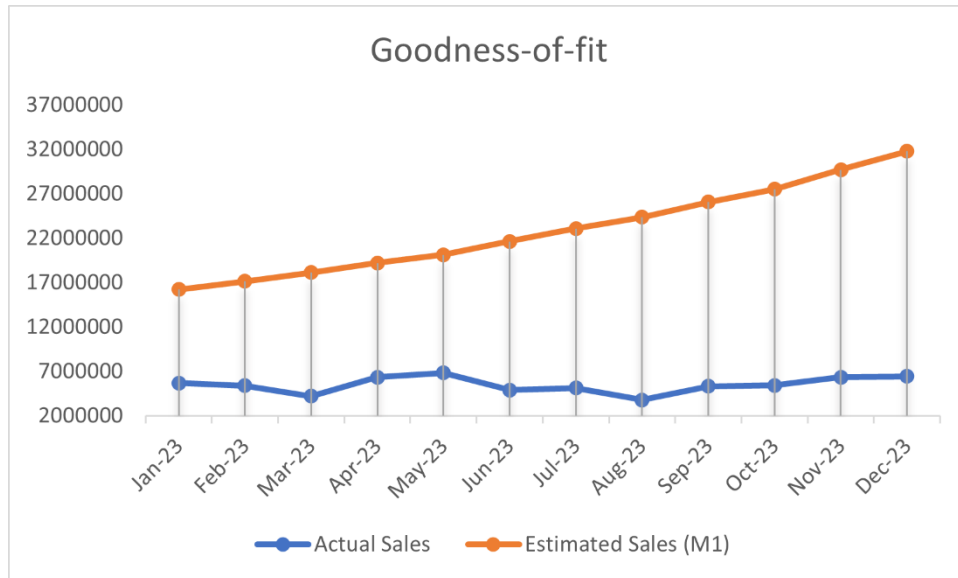


Figure 41, “Time series plot of forecasted Wheat Beer sales”

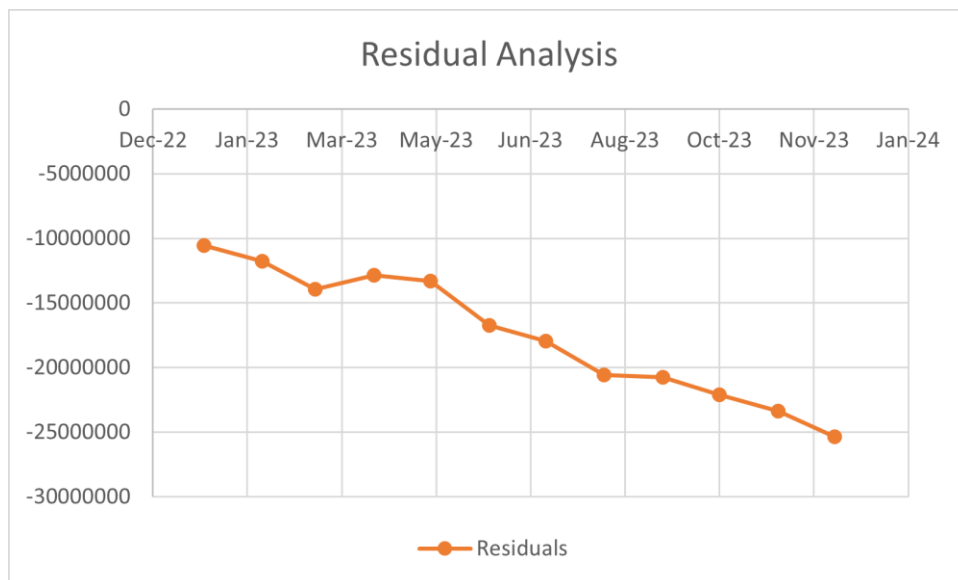


Figure 42, “Residual Analysis of product Wheat Beer”

4.9 EWMA Model Implementation

The following sections will introduce the EWMA model for each product, utilizing Excel’s Solver tool to determine the optimal λ value that minimizes the MAPE metric. Graphical representations will then be provided to compare the results of the EWMA model with those from the previously applied MLR M_1 models for each product. These comparisons will aid in evaluating the effectiveness of each forecasting method and selecting the most appropriate approach.

The same approach will be consistently applied across all products. As outlined in Chapter 4.8, the sales data will be divided into estimation and forecasting samples. The EWMA

model, defined by equation (3.2.1), will initially be run with a randomly selected smoothing factor λ . Using Excel's Solver, the optimal λ value will be identified by minimizing the MAPE *within the estimation sample*. Once the optimal value for λ is determined, the final version of the EWMA model will be used to generate sales predictions for the forecasting sample of each product. Finally, the results from this method will be visually compared to those from the MLR model to facilitate a thorough evaluation of both approaches.

4.9.1 EWMA for product Ale

The equation below represents the EWMA model applied to product **Ale**, along with the corresponding optimal value of the λ parameter, determined using Excel's Solver tool.

$$EWMA(\lambda): \hat{Y}_{t+1} = (1 - 0.9609)Y_t + 0.9609\hat{Y}_t \quad (4.9.1.1)$$

Figure 43 and **44** present the visual comparison of the EWMA model's fit, showcasing both forecasting methods—MLR M_1 and EWMA ($\lambda=0.9609$)—as applied to the product's forecasting sample. Additionally, **Figure 45** illustrates the errors generated by each model. This graphical analysis aims to consolidate the results of the forecasting methods and facilitate an effective comparison between the two models.

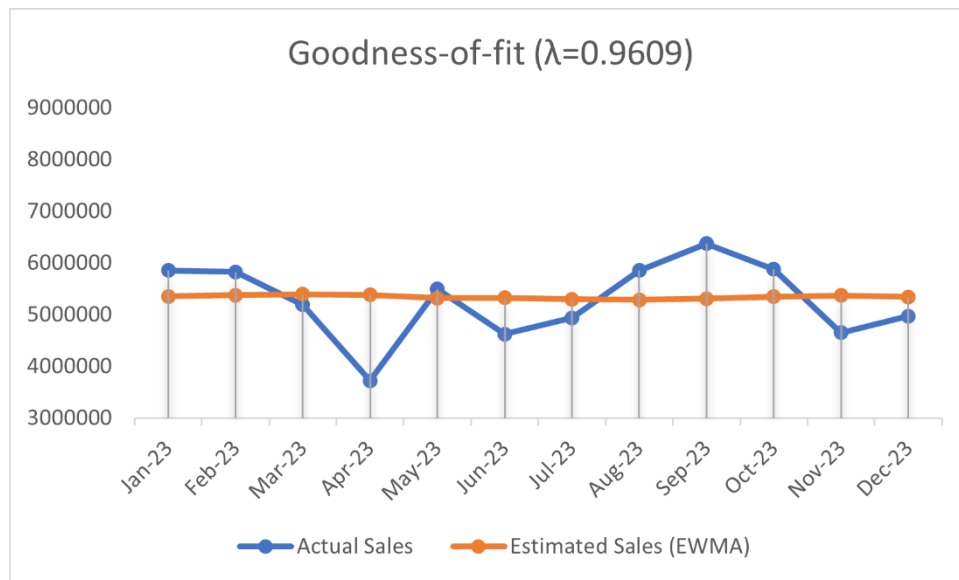


Figure 43, “Time series plot of forecasted Ale sales (EWMA)”

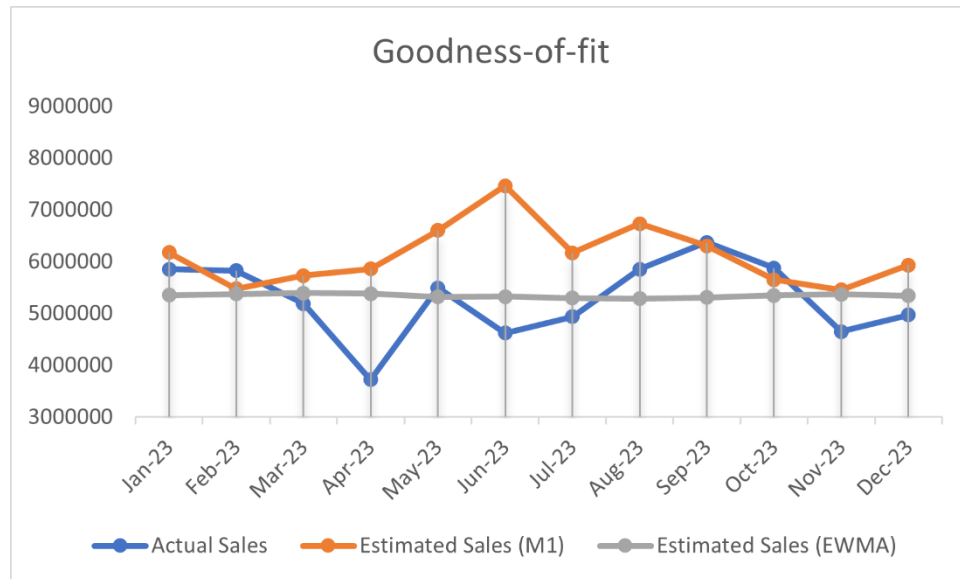


Figure 44, “Graphical presentation of forecasting models for product Ale”

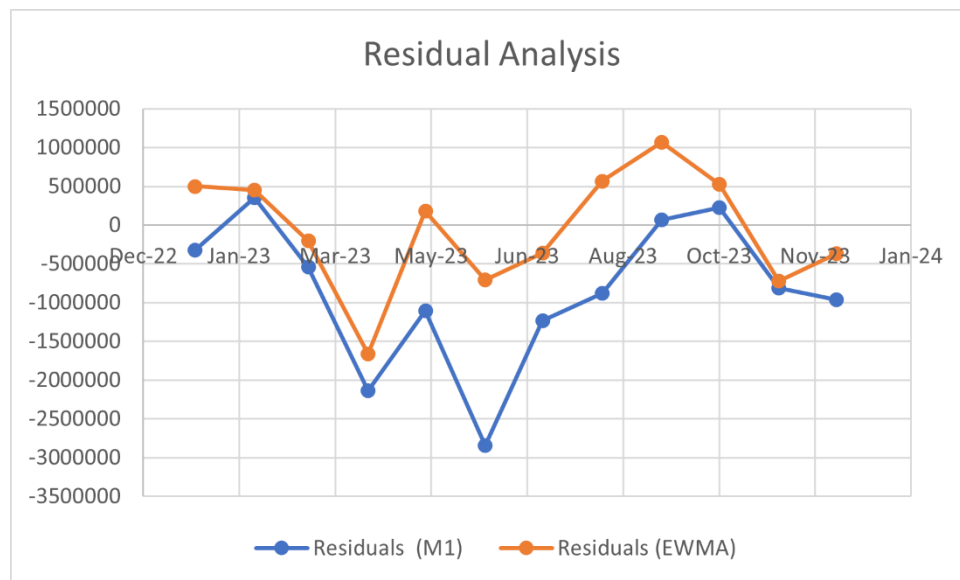


Figure 45, “Residual Analysis of forecasting models for product Ale”

The graphs highlight the EWMA model’s limitation in capturing sales fluctuations, primarily due to the elevated smoothing parameter determined by the Solver tool. This parameter results in overly smoothed sales forecasts that fail to account for short-term variations during the performance period. Additionally, the error patterns in the M_1 model closely resemble those of the EWMA model, indicating that neither model demonstrates a clear advantage over the other in terms of accuracy.

4.9.2 EWMA for product IPA

The equation below represents the EWMA model applied to product **IPA**, along with the corresponding optimal value of the λ parameter, determined using Excel’s Solver tool.

$$EWMA(\lambda): \hat{Y}_{t+1} = (1 - 0.9336)Y_t + 0.9336\hat{Y}_t \quad (4.9.2.1)$$

Similar to the analysis conducted for product **Ale**, **Figures 46-48** display the graphical representations of the forecasting techniques applied to product **IPA**. These graphs illustrate the performance of both the MLR M_1 and EWMA ($\lambda=0.9336$) models, highlighting the fit of the models and the associated prediction errors.

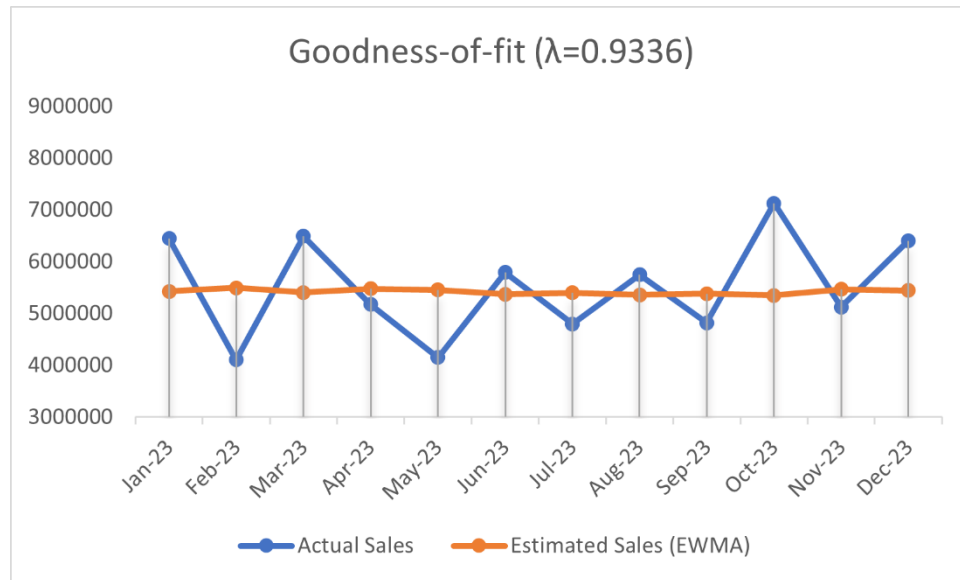


Figure 46, “Time series plot of forecasted IPA sales (EWMA)”

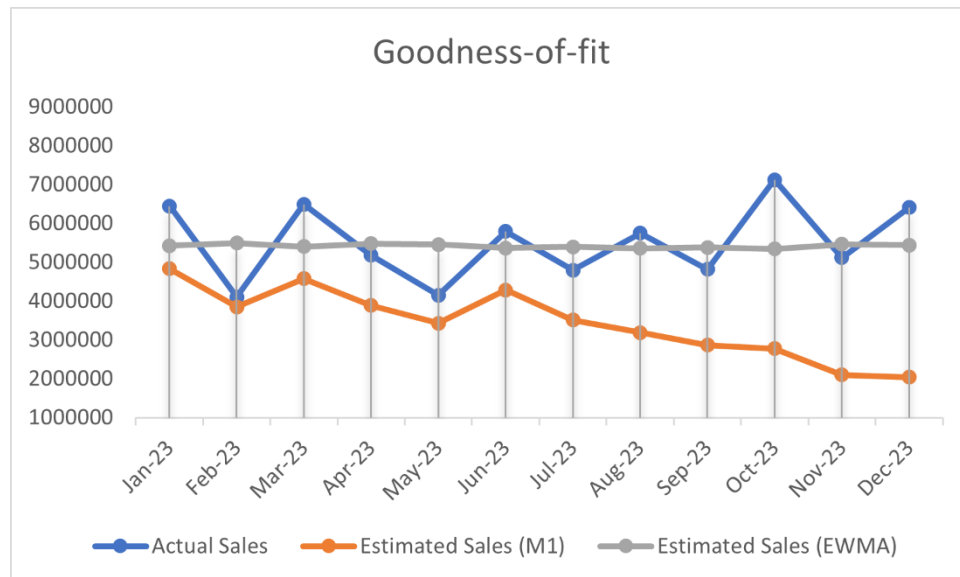


Figure 47, “Graphical presentation of forecasting models for product IPA”

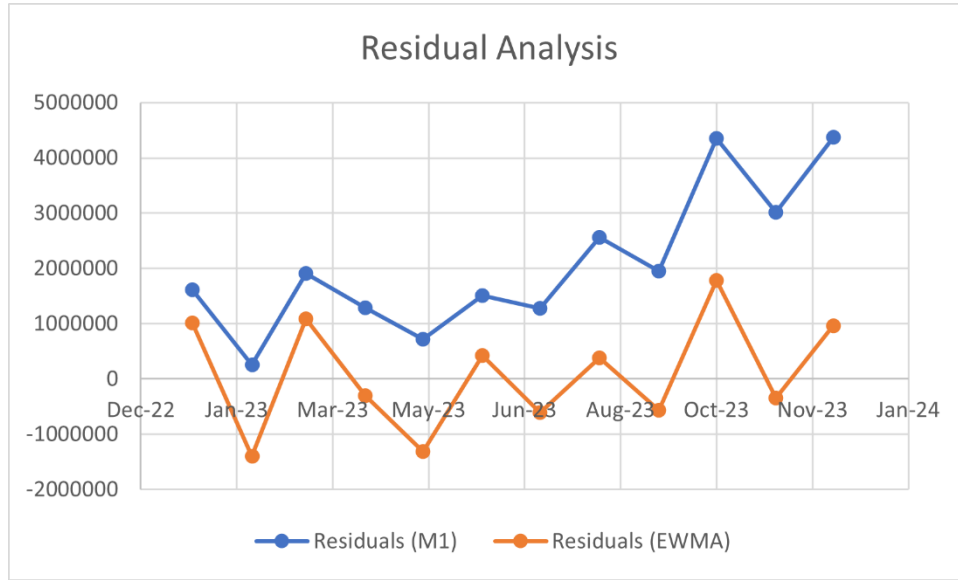


Figure 48, “Residual Analysis of forecasting models for product IPA”

It is evident from the preceding graphs, that the EWMA model fails to reflect the sales fluctuations seen during the performance period. Additionally, the errors from the M_1 model remain positive for entirety of the period, suggesting a persistent underestimation of the actual sales figures by the model.

4.9.3 EWMA for product Lager

The equation below represents the EWMA model applied to product **Lager**, along with the corresponding optimal value of the λ parameter, determined using Excel’s Solver tool.

$$EWMA(\lambda): \hat{Y}_{t+1} = (1 - 0.9388)Y_t + 0.9388\hat{Y}_t \quad (4.9.3.1)$$

Figures 49, 50 and 51 present the visual comparisons of the forecasting methods applied to product **Lager**. The charts illustrate the performance of both the MLR M_1 and EWMA ($\lambda=0.9388$) models, showcasing their predictive accuracy and the resulting error patterns.

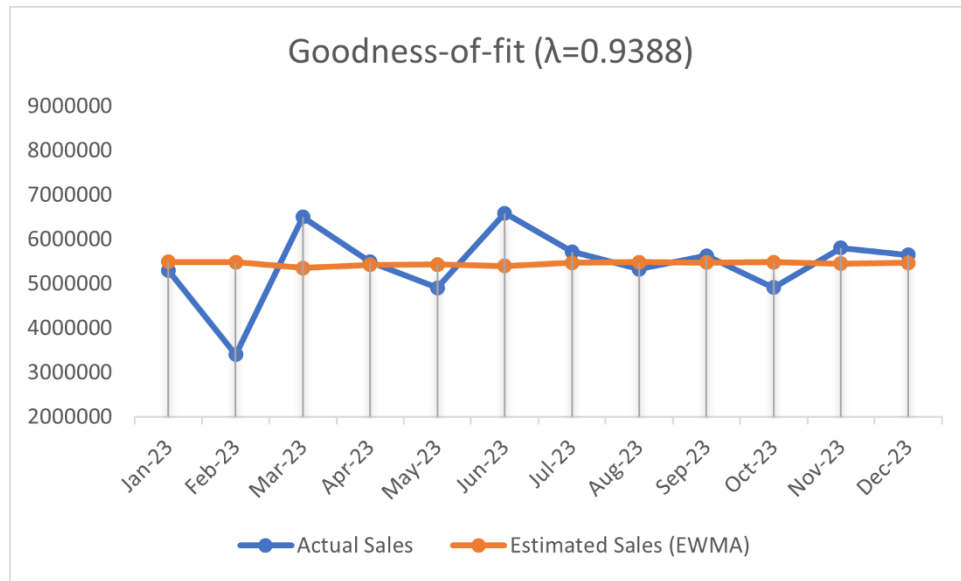


Figure 49, “Time series plot of forecasted Lager sales (EWMA)”

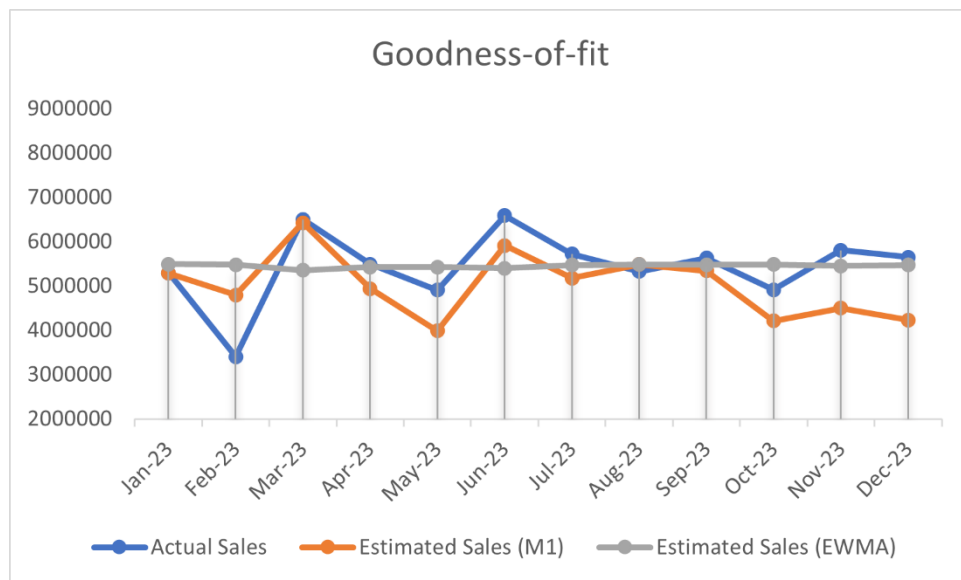


Figure 50, “Graphical presentation of forecasting models for product Lager”

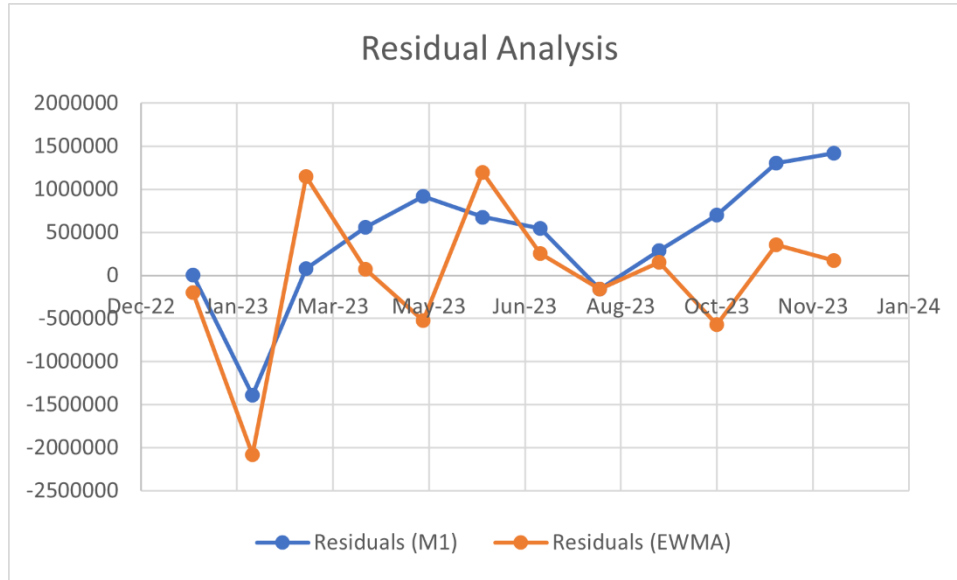


Figure 51, “Residual Analysis of forecasting models for product Lager”

The previous graphs reveal some noteworthy insights. The EWMA model for product **Lager** appears to struggle with accurately reflecting sales volatility. The large smoothing parameter emphasizes older data, which limits the model’s ability to respond to recent fluctuations. Conversely, the forecasting results from the MLR M_1 model seem to better capture the sales variations observed during the performance period.

4.9.4 EWMA for product **Pilsner**

The equation below represents the EWMA model applied to product **Pilsner**, along with the corresponding optimal value of the λ parameter, determined using Excel’s Solver tool.

$$EWMA(\lambda): \hat{Y}_{t+1} = (1 - 0.9959)Y_t + 0.9959\hat{Y}_t \quad (4.9.4.1)$$

Figures 52-54 below present the graphs for the forecasting methods applied to product **Pilsner**. The graphs highlight the EWMA model’s difficulty in capturing sales fluctuations, which can be attributed to the high smoothing parameter value determined by the Solver tool. This results in sales forecasts that smooth out short-term variations in the data. Additionally, the error patterns from the M_1 model are comparable to those of the EWMA model, suggesting that neither model outperforms the other in terms of forecasting accuracy.

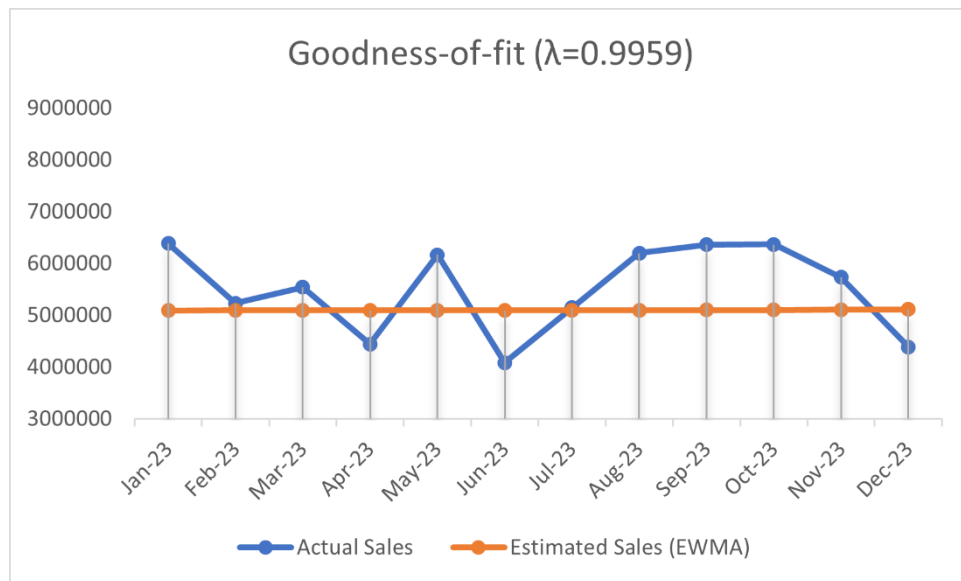


Figure 52, “Time series plot of forecasted Pilsner sales (EWMA)”

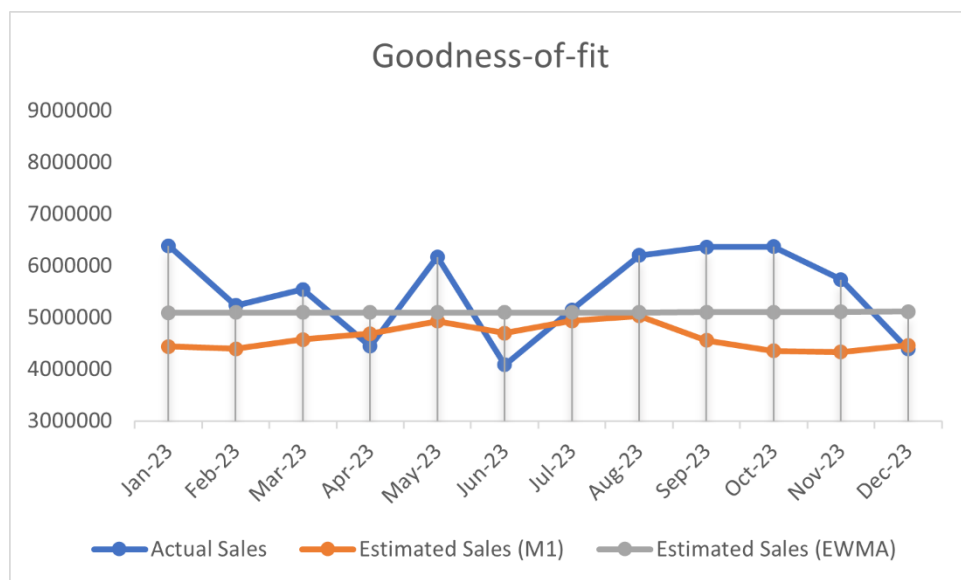


Figure 53, “Graphical presentation of forecasting models for product Pilsner”

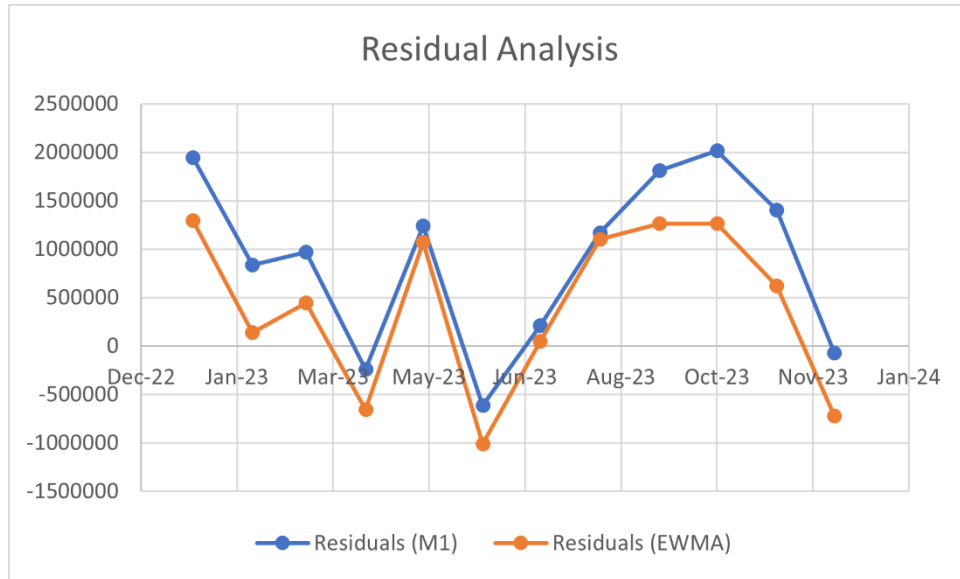


Figure 54, “Residual Analysis of forecasting models for product Pilsner”

4.9.5 EWMA for product **Porter**

The equation below represents the EWMA model applied to product **Porter**, along with the corresponding optimal value of the λ parameter, determined using Excel’s Solver tool.

$$EWMA(\lambda): \hat{Y}_{t+1} = (1 - 0.8830)Y_t + 0.8830\hat{Y}_t \quad (4.9.5.1)$$

Figures 55, 56 and 57 displays the graphical results for the forecasting techniques applied to product **Porter**. Notably, the EWMA model fails to adequately capture sales fluctuations, while the M_1 model appears to be more effective in this respect. However, the forecasting errors from both models are quite similar, indicating that neither model consistently overestimates nor underestimates the actual sales figures.

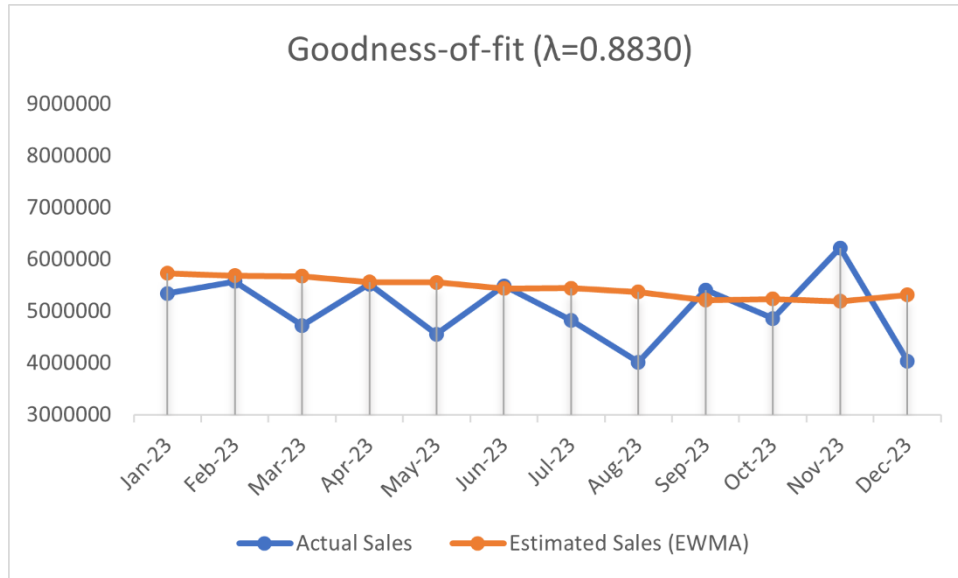


Figure 55, “Time series plot of forecasted Porter sales (EWMA)”

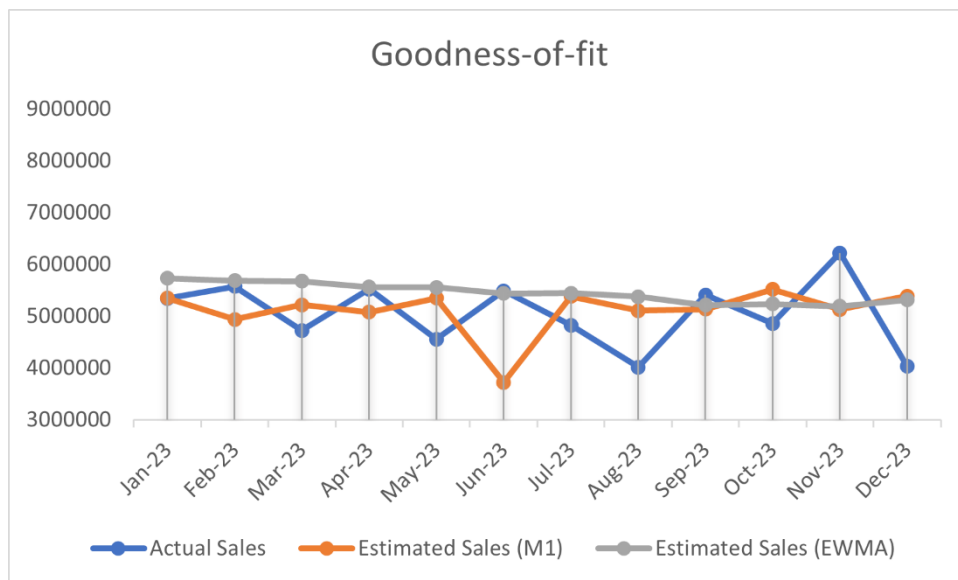


Figure 56, “Graphical presentation of forecasting models for product Porter”

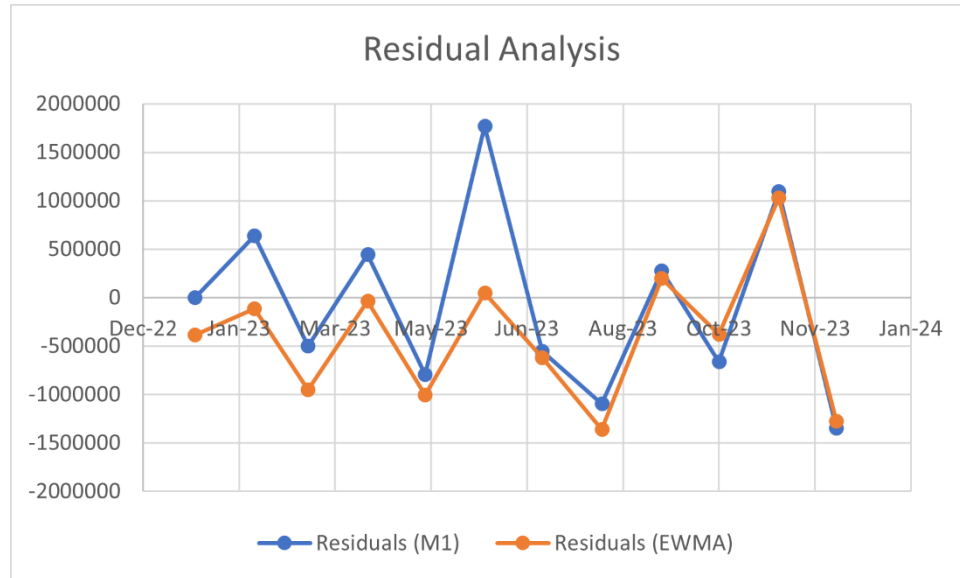


Figure 57, “Residual Analysis of forecasting models for product Porter”

4.9.6 EWMA for product Sour

The equation below represents the EWMA model applied to product **Sour**, along with the corresponding optimal value of the λ parameter, determined using Excel’s Solver tool.

$$EWMA(\lambda): \hat{Y}_{t+1} = (1 - 0.9370)Y_t + 0.9370\hat{Y}_t \quad (4.9.6.1)$$

Figures 58-60 showcase the graphs representing the forecasting methods applied to product **Sour**.

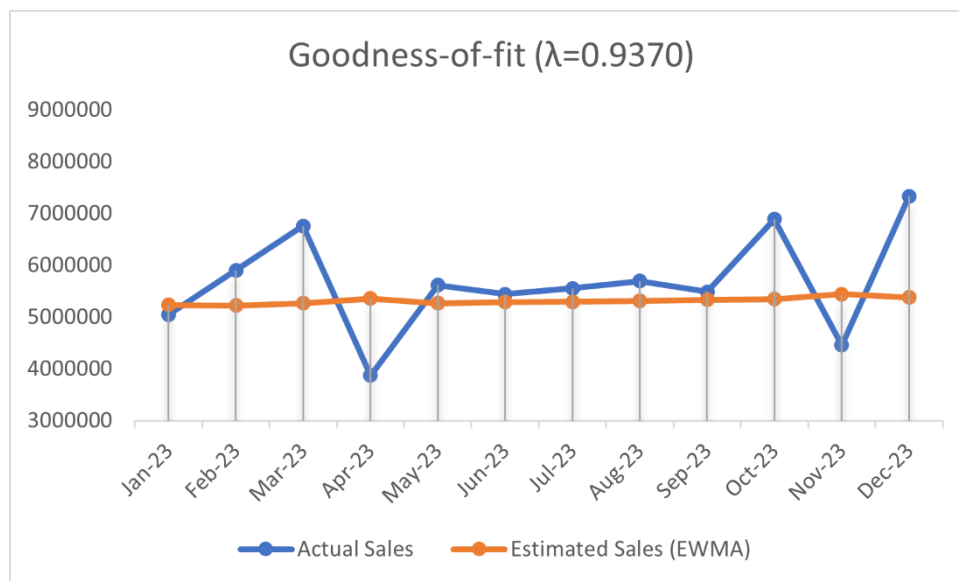


Figure 58, “Time series plot of forecasted Sour sales (EWMA)”

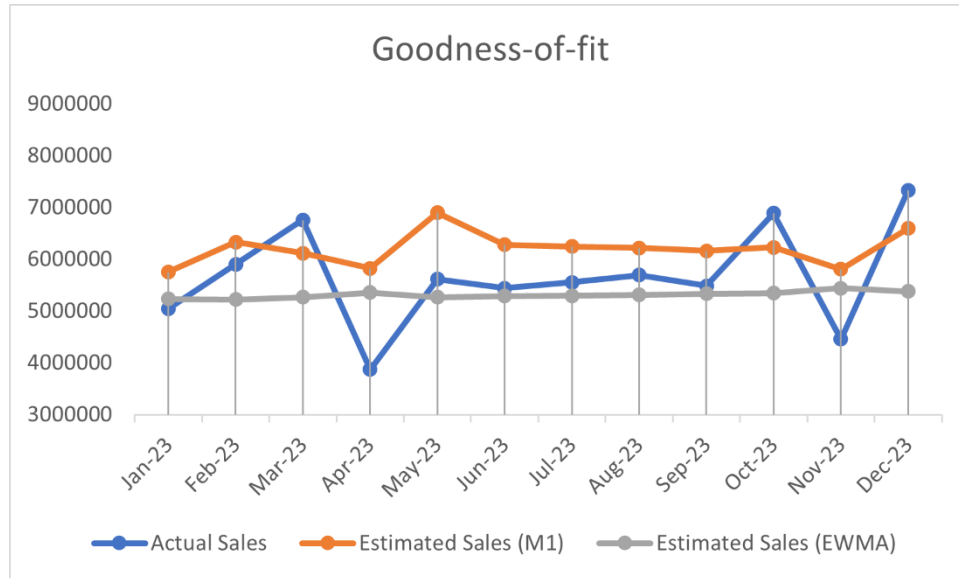


Figure 59, “Graphical presentation of forecasting models for product Sour”

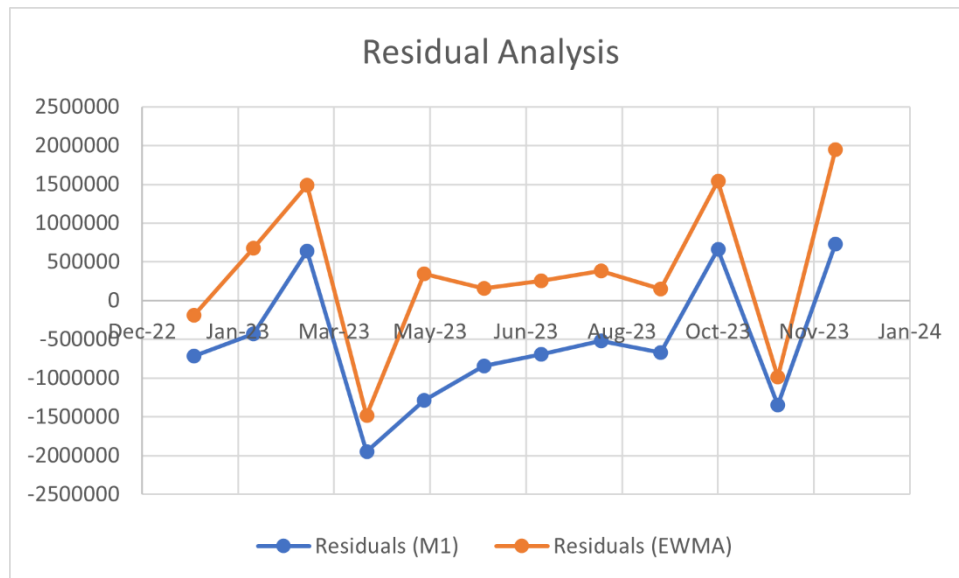


Figure 60, “Residual Analysis of forecasting models for product Sour”

The previous graphs provide valuable insights. In particular, the EWMA model for product **Sour** fails to effectively capture the sales fluctuations. The high smoothing parameter value results in a greater emphasis on older data, preventing the model from detecting sudden shifts in demand. Additionally, the error graphs indicate that both models produce similar forecasting errors, showing no significant differences between them.

4.9.7 EWMA for product **Stout**

The equation below represents the EWMA model applied to product **Stout**, along with the corresponding optimal value of the λ parameter, determined using Excel’s Solver tool.

$$EWMA(\lambda): \hat{Y}_{t+1} = (1 - 1.0000)Y_t + 1.0000\hat{Y}_t \quad (4.9.7.1)$$

Figures 61-63 below present the graphs for the forecasting methods applied to product Stout.

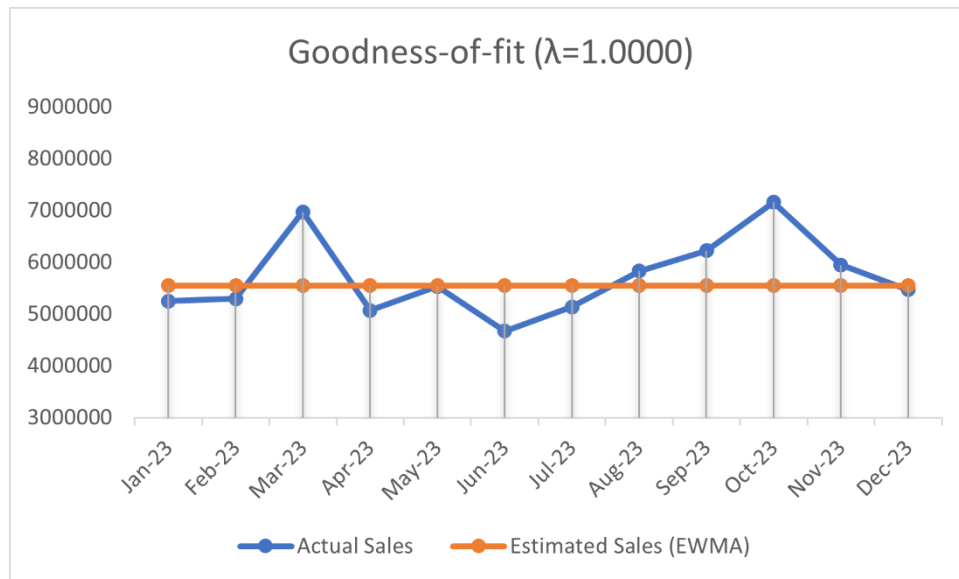


Figure 61, “Time series plot of forecasted Stout sales (EWMA)”

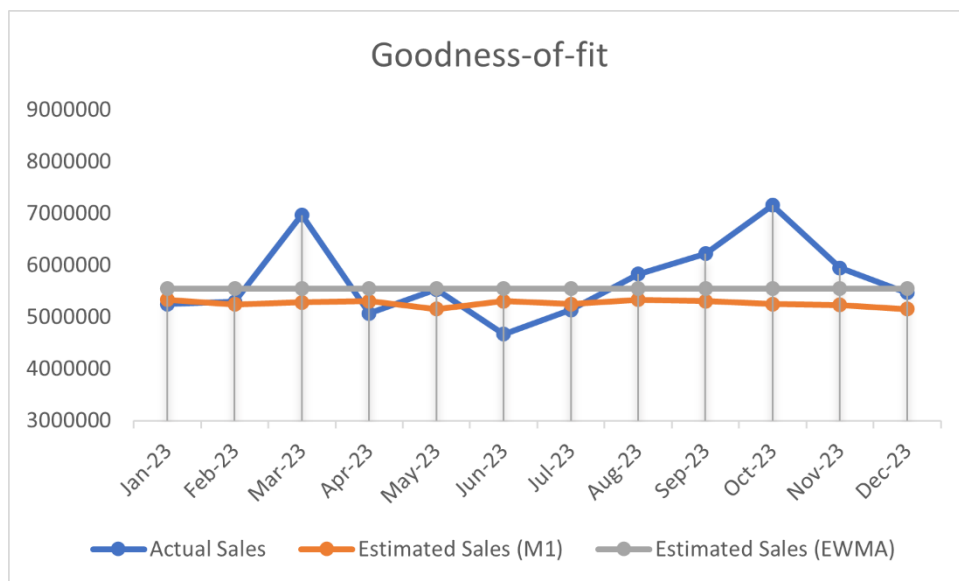


Figure 62, “Graphical presentation of forecasting models for product Stout”

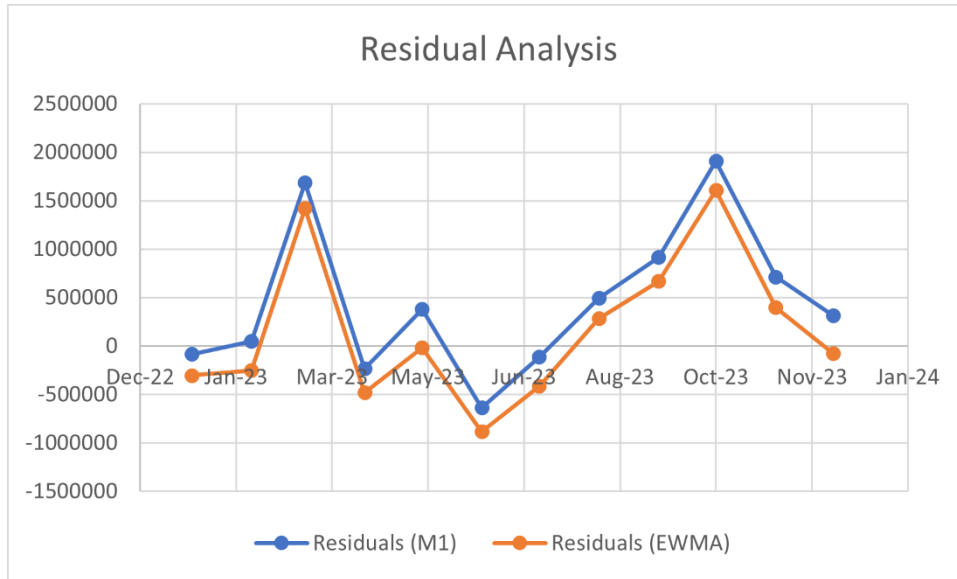


Figure 63, “Residual Analysis of forecasting models for product Stout”

The graphs presented earlier provide valuable insights into the performance of the models and their residuals. The λ smoothing parameter's high value in the EWMA method indicates the model's tendency to adjust gradually, reflecting its stable and consistent nature. This slower response to sudden changes in the time series data, as outlined in Chapter 3.2, causes the model to give more weight to older observations rather than recent data. Additionally, the error graphs show that the forecasting errors from both models are quite similar, with no significant differences between them.

4.9.8 EWMA for product **Wheat Beer**

The final product analyzed for the results and performance of the EWMA model is product **Wheat Beer**. The equation below represents the EWMA model applied to product **Wheat Beer**, along with the corresponding optimal value of the λ parameter, determined using Excel's Solver tool.

$$EWMA(\lambda): \hat{Y}_{t+1} = (1 - 0.7944)Y_t + 0.7944\hat{Y}_t \quad (4.9.8.1)$$

Figures 64-66 below present the graphs for the forecasting methods applied to product **Wheat Beer**.

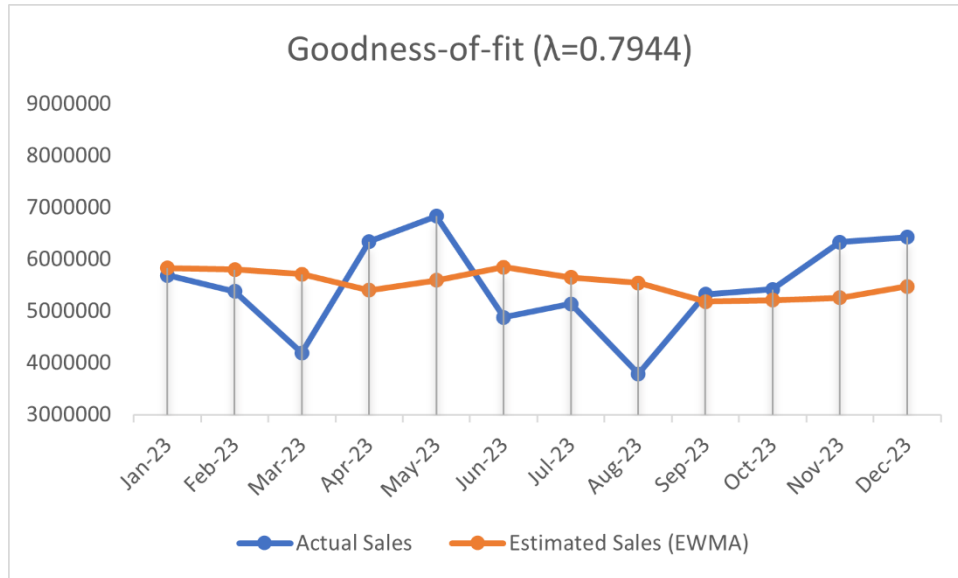


Figure 64, “Time series plot of forecasted Wheat Beer sales (EWMA)”

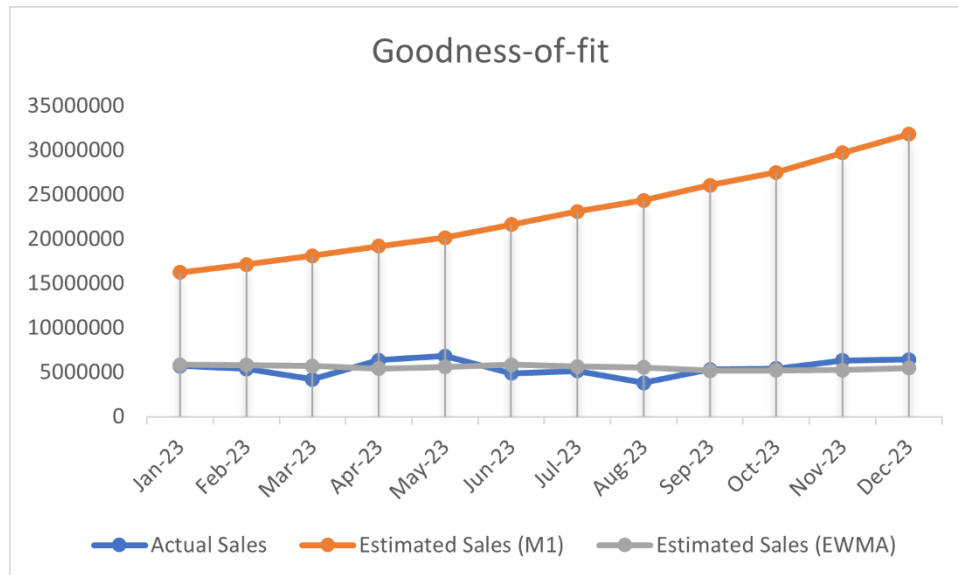


Figure 65, “Graphical presentation of forecasting models for product Wheat Beer”

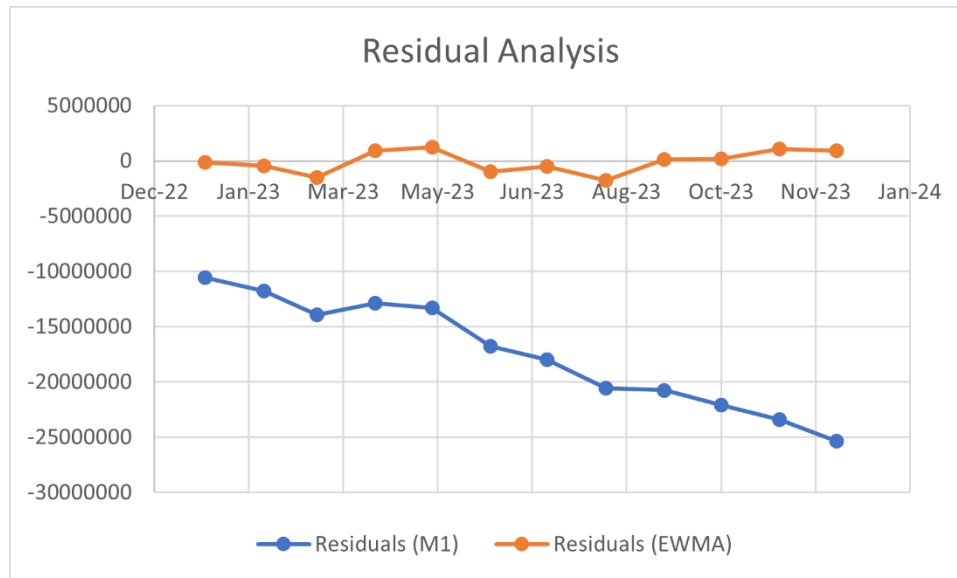


Figure 66, “Residual Analysis of forecasting models for product Wheat Beer”

The graphs reveal that the EWMA model struggles to capture sales fluctuations, primarily due to the high value of the smoothing parameter determined by Excel’s Solver tool. This results in smoother sales predictions that fail to account for short-term variations observed during the performance period. Furthermore, the errors from the EWMA model remain consistently near zero, whereas the M_1 model’s errors stay negative throughout the entire forecasting period.

4.10 Forecasting Performance and Accuracy

At the conclusion of the analysis, **Tables 38** and **39** provide a summary of the MAE and MAPE results obtained from the MLR and EWMA models applied to the forecasting samples. Following the classification framework proposed by Lewis (1982), the MAPE values are categorized to evaluate the accuracy of the forecasts, using established thresholds to determine the effectiveness of each forecasting approach.

- $\text{MAPE} < 10\%$, highly accurate forecasting
- $10\% < \text{MAPE} < 20\%$, good forecasting
- $20\% < \text{MAPE} < 50\%$, reasonable forecasting
- $\text{MAPE} > 50\%$, inaccurate forecasting

Products	R ²	MAE	MAPE
Ale	55.11%	956738.2301	20.22%
IPA	63.32%	2069086.8432	35.75%
Lager	58.89%	670365.9232	13.40%
Pilsner	32.17%	1043499.0640	17.79%
Porter	54.58%	764994.7790	15.69%
Sour	34.75%	873951.3807	16.94%
Stout	32.98%	628124.0921	10.15%
Wheat Beer	43.89%	17439929.8834	327.65%

Table 38 “R², MAE and MAPE results for MLR model M_1 ”

Products	Optimal λ	MAE	MAPE
Ale	0.9609	609591.1265	12.42%
IPA	0.9336	847405.9649	15.73%
Lager	0.9388	573264.3030	11.96%
Pilsner	0.9959	803796.0597	14.47%
Porter	0.8830	616729.9534	13.27%
Sour	0.9370	800982.5371	14.16%
Stout	1.0000	567344.1667	9.49%
Wheat Beer	0.7944	822933.5793	16.17%

Table 39 “Optimal λ , MAE and MAPE results for EWMA model”

The summarized forecasting accuracy results presented in the tables offer valuable information on the effectiveness of the MLR model M_1 and the EWMA model across various products. For products like **Pilsner**, **Porter**, **Sour** and **Stout**, the MAPE values reveal that both models achieve similar levels of accuracy. This suggests that either model can be reliably used for forecasting these products, as they generate comparable predictions.

In the case of products **Ale**, **IPA** and **Lager**, the MAPE results show that both models deliver precise forecasts, though the EWMA model displays a slight edge, making it a more suitable option for future sales estimation. Additionally, for product **Wheat Beer**, the EWMA model clearly outperforms the MLR model, indicating that it is the more effective choice for forecasting sales in these instances.

5. Main Findings

Building upon the research methodology discussed in Chapter 3, this chapter focuses on synthesizing the results and addressing the research questions outlined in Chapter 1.4. The findings related to the products studied will be presented in detail, offering valuable insights that can help in various aspects. These insights may assist in effectively managing excess inventory that ties up a significant portion of the company's capital, minimizing unexpected stock shortages and enabling better planning and decision-making. Each research question will be presented, followed by its corresponding answer.

What are the key patterns and statistical characteristics of the sales time series for the products? Which of these statistical attributes have the most significant impact on the sales trends over time? Are there particular products that exhibit more pronounced seasonal effects?

In the initial phase of the analysis, the sales time series for each product were visually represented through time series graphs, histograms and monthly boxplots. These visualizations offered initial insights into trends, variability and seasonal patterns. Following this, key statistical properties, such as central tendency, variability, skewness and kurtosis, were computed using Excel's descriptive statistics tool to quantify the attributes of the data. The investigation into the presence of trends and seasonal effects was then conducted through multiple linear regression (MLR) models, which incorporated time trends, monthly dummy variables and autoregressive lag terms. The inclusion of lag variables facilitated the identification of short-term memory effects in the sales data. By synthesizing insights from visual analysis and regression results, a more comprehensive understanding of the sales patterns was achieved.

The sales time series of **Ale** demonstrated no significant linear or quadratic trends, nor were there meaningful seasonal patterns or short-memory effects. Despite occasional extreme observations, **Ale**'s sales remained stable, fluctuating consistently around the mean. For **IPA**, the time series exhibited stability without evident trends or strong seasonal effects. However, a short-memory characteristic was identified, indicating that recent months' sales had a statistically significant influence on future demand. The sales of **Lager**, on the other hand, showed pronounced seasonal effects, particularly in the summer months of July and August. This seasonal demand aligns with expected consumption patterns for the product. Although no trends were detected, the presence of short-memory effects emphasized the importance of recent sales in forecasting **Lager**'s demand.

Pilsner's sales time series reflected a consistent pattern without significant trends, seasonality or short-term dependencies, suggesting a steady demand profile over time. In contrast, **Porter** exhibited a clear positive linear trend in its sales, indicative of steady growth. However, this growth showed signs of deceleration, as captured by the negative quadratic trend coefficient. Neither seasonality nor short-memory effects were evident in **Porter**'s sales. **Sour** displayed a prominent seasonal effect, particularly during summer months, with August standing out as a peak period. This seasonality is likely driven by consumer preferences during warmer months. No significant trends or short-memory patterns were identified in **Sour**'s sales, emphasizing its largely predictable seasonal performance.

The sales time series of **Stout** revealed stable demand without notable trends, seasonal variations or short-memory effects, suggesting a consistent performance throughout the analyzed period. Similarly, **Wheat Beer** exhibited no discernible trends or short-memory characteristics. While its sales showed occasional peaks and troughs, any seasonal influences appeared moderate and sporadic, with no consistent or pronounced patterns.

In summary, the analysis revealed that products like **Lager** and **Sour** displayed distinct seasonal effects, while others, such as **Pilsner** and **Stout**, exhibited stability without seasonal or trend-driven fluctuations. Short-memory effects were identified in products like **IPA** and **Lager**, highlighting the influence of recent sales on future performance. **Porter** stood out as the only product with a positive growth trend, albeit with a slowing rate. These findings provide a comprehensive understanding of the sales dynamics, offering valuable insights for demand forecasting and strategic decision-making.

Is there evidence of interdependence in the sales patterns across various product types?

The primary aim of this research question was to investigate and uncover insights regarding potential interdependencies among the sales patterns of various product types within the company's portfolio. Understanding these interactions is critical for enhancing production planning, optimizing inventory management and aligning marketing strategies with observed sales dynamics. To explore these relationships, the MLR model incorporating cross-product sales data was utilized. While the results indicate that most products exhibit independent sales behaviors, certain products demonstrate cross-dependencies that merit further attention.

Notably, the sales of **Ale** appear to be largely independent of other products' sales, with no

significant relationships observed at the 95% confidence level. However, there is weak evidence of interdependence with **Pilsner** and **Sour** at the 10% significance level, where an increase in the sales of these products could potentially correspond to a proportional increase in **Ale**'s sales. For **Sour**, a stronger cross-dependency was observed with **Ale**, where a rise in **Ale**'s sales could result in a 31.3% increase in **Sour**'s sales, assuming all other factors remain constant. This finding suggests a complementary relationship between these products, which could be leveraged for joint promotional strategies.

The sales of **IPA** also demonstrated a potential weak relationship with **Lager**, with evidence of interdependence at the 10% significance level. This suggests that an increase in **Lager**'s sales may be associated with a modest rise in **IPA**'s demand, possibly due to overlapping consumer preferences during specific periods. For **Lager**, no significant interdependencies with other products were observed, further confirming its stable and independent sales profile.

The analysis of **Stout** revealed minimal cross-dependencies, with a weak relationship with **Sour** at the 10% significance level. A potential increase in **Sour**'s sales could result in a slight rise in **Stout**'s demand, highlighting possible shared consumption contexts. In contrast, the sales of **Wheat Beer** and **Porter** displayed no significant interdependencies with other products, reinforcing the autonomous nature of their demand patterns.

Overall, the findings indicate that while most products exhibit independent sales behavior, there are isolated cases of weak cross-dependencies, particularly between **Ale** and **Sour**, as well as **IPA** and **Lager**. These relationships, though not uniformly significant, highlight opportunities for strategic alignment in marketing and inventory management to capitalize on potential synergies in consumer demand.

What is the usual level of accuracy achieved in forecasting monthly sales? Does this level of accuracy differ between various product categories?

To estimate future sales and evaluate the most suitable forecasting models for the craft beer portfolio, both MLR and EWMA forecasting techniques were employed. The evaluation criteria utilized for comparison were the MAPE scores, which provided a clear measure of each model's forecasting accuracy. By analyzing the performance of these models across the product categories, it became evident that the accuracy levels varied significantly depending on the unique statistical characteristics of each product's sales patterns.

Forecasting Methodology	Ale	IPA	Lager	Pilsner	Porter	Sour	Stout	Wheat Beer
MLR Model M_1	20.22%	35.75%	13.40%	17.79%	15.69%	16.94%	10.15%	327.65%
EWMA (λ)	12.42%	15.73%	11.96%	14.47%	13.27%	14.16%	9.49%	16.17%

Table 40 “Comparison matrix of MAPE rate for all products and forecasting methodologies”

Upon analyzing the results presented in the table, it becomes evident that forecasting accuracy varies significantly across the different product categories, with the EWMA models generally outperforming the MLR model in most cases. For certain product categories, such as **Ale**, **IPA** and **Lager**, the EWMA models demonstrate notably better forecasting performance. The relatively lower MAPE scores for these products suggest that the EWMA model effectively captures the underlying patterns in their sales data, providing a more accurate representation of future trends. Conversely, the MLR model’s performance for these products is less satisfactory, as indicated by higher MAPE scores, reflecting its inability to adequately account for key factors influencing sales dynamics.

For products like **Pilsner**, **Porter**, **Sour** and **Stout**, the EWMA models continue to exhibit superior accuracy, albeit with marginal differences compared to the MLR models. This suggests that while both methodologies are capable of producing reasonable forecasts for these categories, the EWMA model is slightly better suited due to its ability to adapt to subtle fluctuations in sales data. However, the relatively close performance of the two models for these products implies that their sales patterns may be less complex or more stable over time, requiring fewer dynamic adjustments in the forecasting process.

The most pronounced contrast between the two models is observed in the case of **Wheat Beer**. Here, the MLR model fails to produce a meaningful forecast, as reflected in its extremely high MAPE score. This highlights the model’s inadequacy in capturing the product’s sales variability and the potential omission of critical variables that drive its demand. On the other hand, the EWMA model successfully achieves a significantly lower MAPE score, indicating its capability to handle the unique characteristics of this product’s sales data.

What impact did the Covid-19 pandemic have on sales and the overall sales patterns of the products analyzed?

Finalizing the thesis research, an investigation was conducted to assess the potential impact of the Covid-19 pandemic on the craft beer products produced by the brewery and distributed in the market. The study focused on evaluating the Covid-19 effect over the

period from March 2020 to April 2022 to ascertain its potential impact on these products' sales.

The outcomes from the MLR model used in Chapter 4.6 indicate that the dummy variable for the Covid-19 pandemic, $Covid_t$, has a high p-value, suggesting that it is not statistically significant. Consequently, this implies that the examined products were not significantly impacted by the outbreak of the pandemic. There were no substantial changes in sales patterns attributable to the pandemic for any of the products analyzed during the specified period, holding all other factors constant.

6. Conclusions and Future Research

The influence of the craft beer sector on the broader supply chain, encompassing production, distribution and consumption, is increasingly significant within the EU and the local market. This sector has shown substantial growth, contributing notably to the economy. However, the outbreak of the Covid-19 pandemic in early 2020 posed significant challenges, introducing uncertainty and disrupting the established sales patterns across various industries, including craft beer.

The current study aimed to analyze and forecast the sales patterns of eight different craft beer products using advanced time series methods. The goal was to enhance the brewery's supply chain operations, particularly in order and production planning. Concluding this dissertation in the domain of sales forecasting and market analysis in the spirits and alcoholic beverages industry, it is crucial to acknowledge certain limitations encountered. These include the limited availability of comprehensive qualitative data and the constraints of the study period, which may have influenced the depth of analysis. Suggestions for future research in sales forecasting and market analysis are thus proposed.

A notable challenge for future research is the integration of qualitative data through targeted surveys conducted with management and key stakeholders. This approach would help identify major drivers of consumer behavior, enriching forecasting models and providing deeper insights. Incorporating judgmental forecasting methods alongside quantitative techniques could lead to more accurate long-term predictions.

Further research should also explore additional modeling approaches such as Holt-Winters exponential smoothing with trend and seasonality, ARIMA, SARIMA, and contemporary methods like Artificial Neural Networks (ANN) and Machine Learning (ML). While ANN models have demonstrated strong predictive capabilities in financial and econometric applications, their effectiveness depends on proper model evaluation. Ensuring statistical adequacy is crucial, as neural networks can be sensitive to sample characteristics and prone to overfitting. Therefore, employing robust diagnostic tests, such as Lagrange Multiplier methods adapted for neural networks, can help assess model validity and improve forecasting reliability (Thomaidis & Dounias, 2012).

Additionally, incorporating explanatory variables such as price fluctuations, marketing activities (advertising, discounts) and their impact on sales could contribute to the development of more powerful forecasting models with improved accuracy and reliability.

Exploring these variables could yield a comprehensive understanding of sales dynamics.

Finally, it is recommended to extend the research to a broader spectrum of companies within the spirits and alcoholic beverages industry. This comparative analysis could validate whether the findings of the present study hold across different contexts and contribute to a more generalized understanding of sales forecasting in the industry.

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Appendix A: “EWMA in-sample analysis results for products Ale, IPA and Lager”

Month	Ale		IPA		Lager	
	Sales	EWMA (λ)	Sales	EWMA (λ)	Sales	EWMA (λ)
Jan-20	5,450,470	5,486,270	6,121,730	4,839,955	6,040,050	5,644,197
Feb-20	5,859,860	5,484,871	3,409,090	4,952,023	4,920,040	5,668,407
Mar-20	5,078,550	5,499,523	6,041,770	4,824,415	4,876,300	5,622,637
Apr-20	5,494,430	5,483,074	5,340,570	4,905,207	6,966,010	5,576,990
May-20	5,600,720	5,483,518	5,244,100	4,934,101	5,129,720	5,661,944
Jun-20	6,206,990	5,488,097	5,047,850	4,954,675	5,129,310	5,629,392
Jul-20	5,801,430	5,516,187	4,712,720	4,960,859	5,833,730	5,598,807
Aug-20	5,521,440	5,527,332	6,217,110	4,944,390	5,805,150	5,613,175
Sep-20	4,814,310	5,527,102	4,745,740	5,028,857	5,872,500	5,624,916
Oct-20	6,221,600	5,499,251	6,614,550	5,010,068	4,747,670	5,640,059
Nov-20	5,495,040	5,527,475	4,567,370	5,116,553	5,934,500	5,585,479
Dec-20	5,237,990	5,526,208	6,063,380	5,080,105	4,766,990	5,606,826
Jan-21	5,824,940	5,514,946	6,729,440	5,145,362	5,114,210	5,555,461
Feb-21	4,022,650	5,527,059	5,191,580	5,250,494	6,514,290	5,528,473
Mar-21	4,702,930	5,468,277	6,112,200	5,246,584	5,496,900	5,588,767
Apr-21	6,733,580	5,438,373	5,777,150	5,304,032	4,636,970	5,583,148
May-21	5,650,270	5,488,980	5,869,150	5,335,432	6,276,580	5,525,279
Jun-21	3,812,500	5,495,282	3,942,070	5,370,853	5,551,910	5,571,229
Jul-21	5,695,950	5,429,531	8,145,450	5,276,029	5,530,520	5,570,048
Aug-21	6,810,260	5,439,941	5,372,130	5,466,465	7,271,240	5,567,630
Sep-21	4,429,490	5,493,483	4,802,830	5,460,204	3,754,200	5,671,825
Oct-21	4,030,590	5,451,910	6,884,930	5,416,576	6,337,030	5,554,541
Nov-21	6,410,000	5,396,375	5,547,650	5,514,027	5,487,520	5,602,399
Dec-21	5,559,060	5,435,980	7,490,190	5,516,258	5,411,030	5,595,373
Jan-22	6,253,580	5,440,789	4,560,320	5,647,263	7,009,020	5,529,053
Feb-22	5,315,230	5,472,547	6,035,650	5,575,125	4,826,710	5,619,569
Mar-22	3,634,390	5,466,400	6,570,460	5,605,689	5,407,550	5,571,077
Apr-22	4,472,020	5,394,819	4,323,330	5,669,718	4,693,620	5,561,076
May-22	7,511,140	5,358,762	6,884,120	5,580,362	5,374,170	5,508,021
Jun-22	5,441,310	5,442,862	5,853,690	5,666,889	6,705,280	5,499,835
Jul-22	5,435,230	5,442,801	4,349,070	5,679,287	5,720,770	5,573,561
Aug-22	3,943,010	5,442,505	5,706,990	5,591,004	5,943,770	5,582,565
Sep-22	5,081,170	5,383,916	5,598,700	5,598,701	5,901,470	5,604,656
Oct-22	4,223,130	5,372,087	3,731,800	5,598,701	5,124,560	5,622,810
Nov-22	5,005,460	5,327,194	5,052,730	5,474,800	4,559,140	5,592,336
Dec-22	6,340,220	5,314,623	5,178,080	5,446,788	4,953,440	5,529,145

Appendix B: “EWMA in-sample analysis results for products Pilsner, Porter and Sour”

Month	Pilsner		Porter		Sour	
	Sales	EWMA (λ)	Sales	EWMA (λ)	Sales	EWMA (λ)
Jan-20	6,177,190	5,047,859	4,880,620	5,619,141	5,391,010	4,833,126
Feb-20	4,472,140	5,052,483	4,503,980	5,532,705	4,648,310	4,868,273
Mar-20	4,262,960	5,050,107	5,714,070	5,412,304	5,541,870	4,854,415
Apr-20	6,595,510	5,046,884	4,577,690	5,447,623	5,401,130	4,897,725
May-20	4,650,718	5,053,224	6,029,150	5,345,806	5,090,840	4,929,440
Jun-20	5,810,940	5,049,869	4,230,410	5,425,784	5,182,260	4,939,609
Jul-20	5,326,010	5,052,985	5,285,880	5,285,879	4,955,850	4,954,896
Aug-20	5,237,180	5,054,103	4,805,050	5,285,879	5,109,410	4,954,956
Sep-20	6,910,930	5,054,852	5,119,460	5,229,604	4,170,340	4,964,687
Oct-20	4,621,940	5,062,452	4,617,360	5,216,713	4,914,640	4,914,642
Nov-20	5,103,190	5,060,648	5,723,360	5,146,565	5,109,410	4,914,642
Dec-20	4,521,790	5,060,823	5,830,310	5,214,073	4,170,340	4,907,469
Jan-21	4,700,320	5,058,615	6,052,530	5,286,197	7,478,200	5,002,883

Feb-21	4,694,890	5,057,148	4,307,250	5,375,888	3,939,940	5,158,831
Mar-21	7,791,770	5,055,665	5,274,750	5,250,815	6,563,380	5,082,039
Apr-21	4,567,820	5,066,868	4,423,360	5,253,617	5,262,570	5,175,365
May-21	5,438,000	5,064,825	5,987,360	5,156,444	5,985,260	5,180,859
Jun-21	4,841,420	5,066,353	4,344,750	5,253,694	5,362,560	5,231,538
Jul-21	4,546,550	5,065,432	4,296,970	5,147,312	4,146,050	5,239,792
Aug-21	6,624,190	5,063,307	5,230,660	5,047,788	4,345,850	5,170,885
Sep-21	5,346,890	5,069,698	6,450,750	5,069,192	5,417,570	5,118,907
Oct-21	4,792,800	5,070,833	6,657,350	5,230,888	5,144,060	5,137,723
Nov-21	5,181,420	5,069,695	6,298,990	5,397,840	5,746,230	5,138,122
Dec-21	4,911,550	5,070,152	5,643,990	5,503,310	5,125,240	5,239,435
Jan-22	5,164,370	5,069,503	7,271,190	5,519,775	4,722,740	5,232,240
Feb-22	5,001,780	5,069,891	6,505,830	5,724,759	4,995,060	5,200,141
Mar-22	5,630,420	5,069,612	5,915,110	5,816,175	3,469,840	5,187,221
Apr-22	4,882,950	5,071,909	5,302,440	5,827,754	5,565,240	5,079,024
May-22	6,822,450	5,071,135	4,514,290	5,766,272	5,879,150	5,109,656
Jun-22	6,608,000	5,078,306	4,769,890	5,619,741	4,331,190	5,158,135
Jul-22	5,570,410	5,084,569	6,043,600	5,520,275	5,463,150	5,106,037
Aug-22	5,604,330	5,086,559	5,235,180	5,581,525	5,035,940	5,128,535
Sep-22	4,726,450	5,088,679	6,320,980	5,540,989	5,519,340	5,122,702
Oct-22	3,958,930	5,087,195	5,441,190	5,632,278	5,019,270	5,147,690
Nov-22	6,237,880	5,082,576	5,348,260	5,609,913	4,445,140	5,139,600
Dec-22	5,908,630	5,087,306	6,874,720	5,579,290	7,274,430	5,095,848

Appendix C: “EWMA in-sample analysis results for products Stout and Wheat Beer”

Month	Stout		Wheat Beer	
	Sales	EWMA (λ)	Sales	EWMA (λ)
Jan-20	6,515,780	5,550,260	6,510,030	4,247,130
Feb-20	5,391,750	5,550,260	4,712,470	4,712,470
Mar-20	5,489,620	5,550,260	8,550,000	4,712,470
Apr-20	5,157,410	5,550,260	6,256,150	5,501,614
May-20	4,032,390	5,550,260	6,246,340	5,656,776
Jun-20	4,763,820	5,550,260	5,143,010	5,778,013
Jul-20	6,814,280	5,550,260	5,153,240	5,647,431
Aug-20	6,302,120	5,550,260	5,401,920	5,545,807
Sep-20	5,108,210	5,550,260	5,792,890	5,721,857
Oct-20	5,243,400	5,550,260	4,292,690	5,736,464
Nov-20	5,617,040	5,550,260	4,161,860	5,439,568
Dec-20	6,588,450	5,550,260	5,098,670	5,176,822
Jan-21	5,112,450	5,550,260	6,843,260	5,160,751
Feb-21	3,133,360	5,550,260	5,170,300	5,506,740
Mar-21	5,825,870	5,550,260	4,357,150	5,437,555
Apr-21	4,544,110	5,550,260	5,413,760	5,215,382
May-21	6,210,650	5,550,260	3,996,740	5,256,176
Jun-21	6,181,460	5,550,260	5,229,870	4,997,187
Jul-21	5,854,010	5,550,260	4,435,550	5,045,036
Aug-21	4,681,350	5,550,260	6,013,660	4,919,702
Sep-21	5,194,710	5,550,260	4,322,000	5,144,662
Oct-21	5,041,460	5,550,260	6,557,840	4,975,491
Nov-21	5,283,670	5,550,260	5,490,870	5,300,883
Dec-21	4,172,750	5,550,260	5,243,620	5,339,952
Jan-22	7,556,320	5,550,260	5,663,650	5,320,142
Feb-22	5,694,060	5,550,260	4,769,770	5,390,781
Mar-22	6,357,340	5,550,260	5,259,960	5,263,077
Apr-22	6,478,840	5,550,260	5,550,780	5,262,436
May-22	6,680,600	5,550,260	6,601,960	5,321,731
Jun-22	4,536,310	5,550,260	6,356,560	5,584,995
Jul-22	7,310,120	5,550,260	5,684,020	5,743,659
Aug-22	5,818,150	5,550,260	6,441,100	5,731,395

Sep-22	4,163,280	5,550,260	5,006,690	5877,337
Oct-22	6,854,770	5,550,260	6,709,380	5698,299
Nov-22	4,807,790	5,550,260	5,692,930	5906,216
Dec-22	5,741,740	5,550,260	5,699,410	5862,356

Appendix D: “EWMA out-of-sample performance results for products Ale, IPA and Lager”

Month	Ale		IPA		Lager	
	ABS Error	%	ABS Error	%	ABS Error	%
Jan-23	500,444	8.55%	1,017,825	15.79%	201,564	3.81%
Feb-23	453,550	7.78%	1,392,015	33.91%	2,078,146	61.06%
Mar-23	201,731	3.89%	1,084,099	16.71%	1,149,005	17.67%
Apr-23	1,659,659	44.56%	300,660	5.81%	69,861	1.27%
May-23	177,939	3.24%	1,307,076	31.50%	512,302	10.62%
Jun-23	704,634	15.25%	423,782	7.32%	1,193,732	18.11%
Jul-23	360,622	7.30%	602,194	12.56%	252,762	4.42%
Aug-23	568,009	9.71%	387,722	6.75%	158,307	2.97%
Sep-23	1,068,155	16.76%	562,320	11.66%	151,625	2.69%
Oct-23	530,079	9.02%	1,779,580	24.97%	571,829	11.64%
Nov-23	721,042	15.51%	343,686	6.71%	356,285	6.14%
Dec-23	369,229	7.43%	967,913	15.10%	174,754	3.09%
MAE	609,591		847,406		573,264	
MAPE	12.42%		15.73%		11.96%	

Appendix E: “EWMA out-of-sample performance results for products Pilsner, Porter and Sour”

Month	Pilsner		Porter		Sour	
	ABS Error	%	ABS Error	%	ABS Error	%
Jan-23	1,295,941	20.29%	385,536	7.21%	188,701	3.74%
Feb-23	136,805	2.61%	112,903	2.03%	680,237	11.53%
Mar-23	447,705	8.08%	950,299	20.12%	1,491,572	22.08%
Apr-23	652,729	14.68%	37,817	0.68%	1,484,859	38.34%
May-23	1,074,324	17.41%	1,002,391	22.01%	348,589	6.21%
Jun-23	1,012,685	24.78%	49,738	0.91%	154,397	2.84%
Jul-23	50,682	0.98%	618,083	12.80%	255,560	4.60%
Aug-23	1,102,644	17.79%	1,361,223	33.93%	382,460	6.72%
Sep-23	1,263,759	19.86%	198,693	3.67%	152,364	2.78%
Oct-23	1,263,645	19.84%	380,502	7.83%	1,542,595	22.39%
Nov-23	621,571	10.84%	1,029,952	16.55%	984,850	22.09%
Dec-23	723,064	16.47%	1,273,623	31.53%	1,945,607	26.55%
MAE	803,796		616,730		800,983	
MAPE	14.47%		13.27%		14.16%	

Appendix F: “EWMA out-of-sample performance results for products Stout and Wheat Beer”

Month	Stout		Wheat Beer	
	ABS Error	%	ABS Error	%
Jan-23	303,530	5.79%	141,778	2.49%
Feb-23	154,680	4.81%	421,363	7.83%
Mar-23	1,421,770	20.39%	1,519,515	36.23%
Apr-23	482,700	9.53%	941,356	14.84%
May-23	10,730	0.31%	1,236,437	18.10%
Jun-23	881,310	18.88%	969,862	19.88%
Jul-23	414,670	8.07%	511,131	9.95%
Aug-23	280,410	4.81%	1,758,163	46.44%
Sep-23	670,720	10.78%	141,063	2.65%
Oct-23	1,607,140	22.45%	207,575	3.83%

Nov-23	395,450	6.65%	1,078,690	17.03%
Dec-23	78,720	1.44%	948,270	14.76%
MAE	567,344		822,934	
MAPE	9.49%		16.17%	

Appendix G: “MLR M_1 out-of-sample performance results for products Ale, IPA and Lager”

	Ale		IPA		Lager	
Month	ABS Error	%	ABS Error	%	ABS Error	%
Jan-23	320,519	5.47%	1,613,479	25.03%	6,015	0.11%
Feb-23	350,465	6.01%	254,041	6.19%	1,393,156	40.93%
Mar-23	542,513	10.45%	1,908,462	29.41%	76,909	1.18%
Apr-23	2,133,920	57.30%	1,289,194	24.91%	556,323	10.12%
May-23	1,106,474	20.13%	723,471	17.44%	918,494	18.72%
Jun-23	2,845,341	61.57%	1,507,075	26.01%	677,238	10.28%
Jul-23	1,232,682	24.96%	1,282,588	26.75%	546,305	9.55%
Aug-23	877,640	15.00%	2,558,379	44.53%	160,501	3.01%
Sep-23	69,560	1.09%	1,953,934	40.53%	286,938	5.10%
Oct-23	228,342	3.88%	4,351,960	61.08%	701,371	14.27%
Nov-23	808,777	17.40%	3,016,471	58.91%	1,304,040	22.46%
Dec-23	964,626	19.40%	4,369,990	68.18%	1,417,101	25.10%
MAE	956,738		2,069,087		670,366	
MAPE	20.22%		35.75%		13.40%	

Appendix H: “MLR M_1 out-of-sample performance results for products Pilsner, Porter and Sour”

	Pilsner		Porter		Sour	
Month	ABS Error	%	ABS Error	%	ABS Error	%
Jan-23	1,945,210	30.46%	462	0.01%	712,427	14.12%
Feb-23	839,593	16.04%	637,258	11.43%	428,283	7.26%
Mar-23	970,312	17.50%	497,733	10.54%	639,246	9.46%
Apr-23	239,553	5.39%	444,465	8.05%	1,950,841	50.37%
May-23	1,242,517	20.14%	793,549	17.42%	1,286,147	22.91%
Jun-23	611,328	14.96%	1,768,428	32.22%	840,657	15.45%
Jul-23	209,243	4.07%	556,484	11.53%	695,474	12.53%
Aug-23	1,169,412	18.87%	1,095,655	27.31%	520,923	9.15%
Sep-23	1,808,754	28.42%	278,865	5.15%	672,279	12.25%
Oct-23	2,014,432	31.63%	659,413	13.58%	662,257	9.61%
Nov-23	1,401,662	24.45%	1,096,706	17.63%	1,347,428	30.22%
Dec-23	69,974	1.59%	1,350,918	33.44%	731,456	9.98%
MAE	1,043,499		764,995		873,951	
MAPE	17.79%		15.69%		16.94%	

Appendix I: “MLR M_1 out-of-sample performance results for products Stout and Wheat Beer”

	Stout		Wheat Beer	
Month	ABS Error	%	ABS Error	%
Jan-23	85,419	1.63%	10,551,028	185.53%
Feb-23	51,226	0.97%	11,762,926	218.71%
Mar-23	1,686,122	24.18%	13,932,937	332.25%
Apr-23	235,625	4.65%	12,853,000	202.67%
May-23	378,380	6.84%	13,311,802	194.89%
Jun-23	636,218	13.63%	16,746,792	343.27%
Jul-23	116,424	2.27%	17,962,104	349.60%
Aug-23	493,860	8.47%	20,565,981	543.25%
Sep-23	917,796	14.75%	20,741,114	389.62%
Oct-23	1,906,789	26.64%	22,101,062	407.85%

Nov-23	713,465	12.00%	23,378,478	369.17%
Dec-23	316,164	5.78%	25,371,934	394.95%
MAE	628,124		17,439,930	
MAPE	10.15%		327.65%	

Author's Statement:

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