Print ISSN: 2765-6934 / Online ISSN: 2765-7027
AJBE website: http://accesson.kr/ajbe
Doi: 10.13106/ajbe.2024.vol14.no3.1

Analyzing the Impact of Weather Conditions on Beer Sales: Insights for Market Strategy and Inventory Management

Sangwoo LEE[1], Sang Hyeon LEE[2]

Received: June 23, 2024. Revised: June 26, 2024. Accepted: June 27, 2024.

Abstract

Purpose: This study analyzes the impact of weather conditions, holidays, and sporting events on beer sales, providing insights for market strategy and inventory management in the beer industry. **Research design, data and methodology:** Beer types were classified into Lagers and Ales, with further subcategories. The study utilized weekly retail sales data from January 2018 to August 2020, provided by Nielsen Korea. An ARMAX model was employed for time-series analysis. **Results:** The analysis revealed that increasing temperatures positively influence sales of Pilsners and Pale Lagers. Conversely, higher precipitation levels negatively affect overall Lager sales. Among Ales, only Stout sales showed a significant decrease with increased rainfall. Sunshine duration did not significantly impact sales for any beer type. Humidity generally had little effect on beer sales, with the exception of Amber Lagers, which showed sensitivity to humidity changes. Holidays and sporting events were found to significantly boost sales across most beer types, although the specific impacts varied by beer category. **Conclusions:** This study offers a detailed analysis of how weather conditions and specific events influence different beer type sales. The findings provide valuable insights for breweries, beer processors, and retailers to optimize their market strategies and inventory management based on weather forecasts and seasonal events. By understanding the consumption patterns of each beer type in relation to environmental factors, businesses can better anticipate demand fluctuations and tailor their operations accordingly.

Keywords : Beer Sales, Weather Conditions, Market Strategy, ARMAX Model, Time Series Analysis

JEL Classification Code : L66, Q13, M12, M21,

1. Introduction

Weather plays a direct or indirect significant role in the demand and sales of products and is also known to have a substantial impact on individual mood changes (Knez et al., 2009; Li et al. 2017). These mood changes are directly connected to consumer behavior, and weather changes such as temperature and precipitation act as meaningful variables in customer-centric business activities (Agnew & Palutikof 1999; Roslow et al., 2000; Parsons, 2001; Cao & Wei, 2005; Murray et al., 2010; Hong et al., 2012). Accordingly, both businesses and academia recognize the importance and potential of predicting consumer behavior based on weather

1 First Author. Master Course, Department of Food and Resource Economics, Korea University, Seoul city. Email: wwewwew31 @gmail.com
2 Corresponding Author. Professor, Department of Food and Resource Economics, Korea University, Seoul City, Email: lsh21c@korea.ac.kr

(Hirche et al., 2021), and many companies implement marketing strategies using weather information (King & Narayandas, 2000; Rosman, 2013). Research on the relationship between weather and product consumption has been conducted across various academic fields (Lee et al., 2018), and recently, numerous studies have directly analyzed the relationship between weather changes and alcohol consumption (Bratina & Fagnel, 2008; Hirche et al., 2021; Tian et al., 2021).

Based on these previous studies, this study aims to analyze the impact of weather factors on domestic beer consumption. The reasons for selecting beer as the subject of the study are as follows. (1) As of 2020, the domestic alcohol market size was approximately 8.8 trillion won in terms of shipment value, with soju and beer accounting for about 81.8% (7.2 trillion won) of the total (Korea Agro-Fisheries & Food Trade Corporation, 2021). (2) Particularly for beer, it accounted for nearly half of the total alcohol market shipment volume in 2018, at 53.8% (Korea Consumer Agency, 2018). This indicates that beer holds a significant share in the domestic alcohol market and is one of the most consumed alcoholic beverages in Korea (Park et al., 2019).

The market comprises various types of beer, and consumption patterns for each type may vary with the seasons. This study aims to investigate the impact of weather on the consumption of different types of beer by categorizing them in detail. Additionally, holidays and sports events, which are likely to significantly influence beer consumption, were also included in the analysis. By analyzing the impact on beer consumption by type, this study is expected to contribute to marketing strategies and inventory management in the alcoholic beverage industry. Therefore, this study aims to provide reference material that can help breweries, beer processing companies, and retailers plan their inventory according to weather trends.

2. Literature Review

Many studies have directly analyzed the relationship between alcohol consumption and weather changes. Looking at studies outside of Korea, Bratina (2008) reported that a 1°C increase in temperature leads to a 4.93% increase in beer sales in Slovenia. Hirche et al. (2021) found that the same temperature increases results in an average 10.2% increase in retail beer sales in some regions of the United States. Additionally, Tian et al. (2021) observed that a 1°C increase in temperature in Beijing results in an average 6% increase in retail alcohol sales.

These studies emphasize that weather affects alcohol consumption, and alcohol consumption responds sensitively to weather changes (Martin et al. 2020; Tian et al. 2021). In Korea, studies by Kim (2012) and Jung et al (2023) are notable. Kim (2012) research focused on soju and beer, which account for the largest share of the domestic alcohol industry. The study found that beer sales decrease by approximately 4% for every additional hour of sunshine, and increase by approximately 2% for every 1°C rise in temperature. This study is significant as it comprehensively examined the sales patterns of various types of alcohol according to seasonal and weather factors. Additionally, Jung et al. (2023) confirmed the influence of humidity, finding that higher humidity levels lead to increased beer sales.

However, previous studies related to domestic beer consumption have mainly focused on beer product selection attributes, product evaluation, consumption behavior, and market segmentation according to consumer characteristics (Kim & Cho, 2007; Yoo et al., 2015; Cho, 2018). Research on the impact of weather changes on beer purchasing behavior is limited in Korea (Kim, 2012; Hong et al., 2012; Jung et al., 2023), with relatively few studies outside of those by Kim (2012) and Jung (2023). Considering the lack of research and the fact that alcohol consumption is sensitively influenced by weather changes, it is deemed necessary to analyze cases of how weather affects beer consumption.

3. Research Methods and Materials

3.1. Data

This study aims to analyze the impact of weather-related exogenous variables (temperature, precipitation, humidity, and sunshine duration) and specific periods (holidays and sports events) on beer consumption, particularly on the sales of detailed categories of Ales and Lagers, using weekly panel data from January 2018 to August 2020. The data and methods used in this study are as follows. Beer sales data were analyzed based on retail data provided by Nielsen Korea. This data comprehensively covers the weekly sales volume (in 10,000 liters) of 506 beer brands sold nationwide from the first week of January 2018 to the first week of August 2020. During the analysis, this study classified beer types into Lagers and Ales. Beers were classified as Lagers if the yeast ferments at the bottom of the container at low temperatures, and as Ales if the yeast ferments at the top of the container at high temperatures (Kwak et al., 2018).

Although there are many types of beer, it is practically impossible to analyze all types. Therefore, this study excluded beer types with low sales volumes and focused only on the top three types with the highest sales volumes included in the raw data. Consequently, the original 75,600 data points were reduced to 52,380. The Ale group included

Wheat beer, Belgian Ale, and Stout, while the Lager group included Pilsner, Pale Lager, and Amber Lager. The sales frequency by type is shown in Table 1.

Table 1: Beer Sales Frequency

Type	Sub-type	Freq.	Percent
Ale	Wheat beer	12,015	22.9
	Belgian Ale	5,535	10.6
	Stout	4,320	8.2
	Sum	21,870	41.8
Lager	Pilsner	12,690	24.2
	Pale Lager	15,660	29.9
	Amber Lager	1,755	4.1
	Sum	30,510	58.2
	Total sum	52,380	100

In this study, we analyzed weather data from the Korea Meteorological Administration covering the period from January 1, 2018, to August 1, 2020, using the national weekly averages. The analysis focused on weather factors reported in previous studies to affect retail sales, particularly beer sales. The weather factors considered in this study include maximum temperature, precipitation, humidity, and sunshine duration. According to the studies by Bratina and Faganel (2008) and Hirche et al. (2021), maximum temperature has been identified as a significant factor influencing alcohol sales. Additionally, research by Li et al. (2017) and Murray et al. (2020) has shown that precipitation, humidity, and sunshine duration can affect retail sales.

To consider the impact of specific social events on beer consumption, this study included periods of national holidays and major sports events such as the World Cup and the Olympics. According to Hirche et al. (2021) research, holidays positively impact alcohol sales. Beer consumption tends to surge during televised sports events compared to average household consumption. During the 2018 FIFA World Cup, the number of shoppers in the beer category increased by 18% compared to the annual average, attracting an additional 1.4 million shoppers (Talking Retail, 2022). During the same World Cup period, about 25% of French people consumed more aperitifs and beer than usual (Statista, 2021). Additionally, CNBC (2017) reported that beer sales reached $600 million during the Super Bowl. These findings suggest a tendency for beer consumption to spike during major sports events, indicating the need to consider changes in beer consumption patterns during specific periods, particularly major sports events, in Korea as well.

To enhance the accuracy of beer consumption forecasts, this study incorporated weekly beer demand patterns and beer consumption during holidays and sports events into the time series model. Dummy variables indicating weeks with holidays and sports events were used in the analysis. Holidays were determined based on the holiday list and dates provided by the Ministry of the Interior and Safety of the Republic of Korea. The analysis used data from January 1, 2018, to August 1, 2020, and divided this period into weekly units to create the 'week' variable. In the table, 'week' indicates which week of a specific year it is. For example, '201801' represents the first week of 2018, and '201806' represents the sixth week of 2018. Here, the 'week' variable sequentially numbers each week. For instance, if the value of the 'week' variable is 1, it indicates the first week of 2018. August 1, 2020, corresponds to the 135th week from January 1, 2018. Therefore, the value 135 in the 'week' variable corresponds to August 1, 2020 (Appendix 1).

3.2. Tables and Figures

In this study, the dependent variable, which is the sales volume of each beer type, was constructed by aggregating the total sales volume of each beer type on a weekly basis. Specifically, this variable was created by grouping and summing the sales data for each type of beer for a given week. For example, for Pilsner beer, the variable representing the total weekly sales volume of Pilsner beer was formed by summing the sales volumes of all Pilsner brands sold in the week with the 'week' variable value of 1. According to the descriptive statistics of the analysis data presented in Table 3, the sales volume of Ales was generally lower than that of Lagers. This reflects the general preference for Lagers over Ales in Korea (Yoo et al., 2015), confirming that the sales volume of Lagers is higher than that of Ales.

Table 2: Descriptive Statistics

Variable	Obs	Mean	Std. dev.	Min	Max
Temperature	135	18.7	9	-0.9	35.5
Rain	135	3.7	5.2	0	26
Humid	135	67.6	10.4	45	91
Sun	135	6.5	3.4	0	13.2
Sport	135	0.1	0.2	0	1
Holiday	135	0.2	0.4	0	1
week	135	68	39	1	135
Wheat	135	78.37	11.74	59.86	104.95
Belgian	135	2.27	1.05	0.35	5.22
Stout	135	20.93	2.7	16.01	31.01
Pilsner	135	160.16	25.21	108.98	228.94
Pale	135	1211.91	181.94	941.35	1844.79
Amber	135	1.42	0.62	0.48	2.58

Note: temperature refers to the weekly average maximum temperature, rain refers to the weekly average precipitation (mm), humid refers to the weekly average humidity (%rh), and sun refers to the weekly average sunshine duration (hr).

4. Methodology

4.1. Unit Root Test

Alcohol consumption is influenced not only by seasonal factors but also by specific days of the week (Lenten & Moosa, 1999; Puljula et al., 2007; Olson et al., 2021). Therefore, future demand estimation should be based on time series analysis that can reflect trends and cycles. Before conducting time series analysis, it is necessary to check the stability of the data used. The Unit Root Test is a method for testing the stability of time series data. Using unstable data for analysis may result in spurious regression. Therefore, to analyze beer sales using time series data, it is essential to test the stability of the data. In this study, the Augmented Dickey-Fuller (ADF) test, which is commonly used and considers trends with autocorrelation, was conducted to determine the stability of the time series.

4.2. ARMAX model

The ARMA (AutoRegressive Moving Average) model is a statistical model used to describe and predict stationary time series data. The ARMA model combines the autoregressive (AR) part and the moving average (MA) part to model time series data. ARMA(p,q) represents a model with parameters p autoregressive terms and q moving average terms (Equation 1). The parameter p indicates the order of the AR (Autoregressive) part, showing the influence of previous values on the current value, while q indicates the order of the MA (Moving Average) part, showing the influence of previous errors on the current value. Y_t represents the time series data of the dependent variable, ϕ_p is the polynomial for the autoregressive part (AR), and θ_q is the polynomial for the moving average part (MA). ϵ_t is a white noise series or error term that is independent, has a mean of 0, and follows a normal distribution with constant variance.

$$Y_t = \epsilon_t + \sum_{i=1}^{p} \phi_i Y_{t-i} + \sum_{i=1}^{q} \theta_i \epsilon_{t-i}$$

$$Where\ \phi_p(B) = 1 - \ \phi_1 B - \cdots \phi_i B^p$$

$$\theta_q(B) = 1 - \ \theta_1 B - \cdots \theta_i B^q$$

Using the Backward Shift Operator B , the ARMA model can be expressed as shown in the equation below

$$\phi_p(B)(Y_t) = \ \theta_q(B)\epsilon_t$$

The ARMAX model is a generalized form of the ARMA model, which can incorporate external input variables (X). This allows for the analysis to consider external factors. In this study, we aim to estimate the factors affecting beer consumption by using the ARMAX model, including weather, public holidays, and sporting events as external variables.

$$\phi_p(B)(Y_t) = \theta_q(B)\epsilon_t + \sum_{i=1}^{k} \beta_i X_{i,t}$$

4.3. Prediction

In this study, a unit root test was conducted to verify the stability of each time series variable. After the unit root test, we aim to explore the optimal model among time series models through the Box-Jenkins procedure. The Box-Jenkins methodology includes steps to identify and estimate the model, determining the order of the time series model. Specifically, the Box-Jenkins method involves three steps: model identification, parameter estimation, and diagnostic checking. Through this process, we aim to construct the optimal time series model. In subsequent stages, we intend to forecast data for future periods based on this analysis. After making predictions, it is necessary to evaluate the accuracy of these forecasts. In this study, RMSPE and Theil's inequality coefficient were used to evaluate predictive accuracy. $\hat{Y}_t$ represents the predicted values, Y_t represents the actual values, and n represents the forecast period.

$$\mathrm{RMSPE} = \sqrt{\frac{1}{\mathrm{n}} \sum_{\mathrm{t=1}}^{\mathrm{n}} \left(\frac{\hat{\mathrm{Y}}_\mathrm{t} - \mathrm{Y}_\mathrm{t}}{\mathrm{Y}_\mathrm{t}} \right)^2} \times 100$$

$$Theil's\ U = \frac{\sqrt{\frac{1}{n}\ \sum_{t=1}^{n} \left(\hat{Y}_t - Y_t\right)^2}}{\sqrt{\frac{1}{n} \sum_{t=1}^{n} (Y_t)^2} + \sqrt{\frac{1}{n} \sum_{t=1}^{n} \left(\hat{Y}_t\right)^2}}$$

Additionally, this study aims to analyze the impact of weather, holidays, and sports events on the beer market using the common analysis method of multiple regression analysis. The results of this analysis will be compared with the time series analysis to evaluate the predictive abilities of both methods. The analysis was conducted using the statistical software Stata/SE version 18.

5. Results and Discussion

5.1. Unit Root Test & Identification

This study constructed a time series-based model to explain the relationship between exogenous variables such as climate and sports events on beer consumption. First, a unit root test was conducted to verify the stability of each time series variable. The test results showed that most of the time series data did not have a unit root and were stable (Appendix 2).

In the next step, it is necessary to find the most suitable time series model for the given time series data and determine the orders of p, d, and q for the ARIMA model. For the beer types, d was set to 0. The selection of p and q was based on the identification of the ARIMAX model using the Auto Correlation Function (ACF) and Partial Auto Correlation Function (PACF) tests. The VIF test results for the exogenous variables used in this study showed a VIF value of 1.6, indicating no multicollinearity issues. To evaluate the model's suitability, the appropriate model was selected based on the Akaike’s Information Criterion (AIC) value, with the model having the lowest AIC value being chosen as the final model. After the identification and optimization process of the model, the factors affecting the sales volumes of various beer items were analyzed through the model, as shown in Tables 3 and 4.

5.2. ARMAX Model

5.2.1 Lager

For Pilsner, examining each coefficient shows that AR(1) and AR(2) are significant at the 5% ,1% significance level, and they positively affect sales volume at the respective time points. This indicates that the first and second lagged autoregressive terms in the ARIMA model are statistically significant predictors of Pilsner sales volume. Additionally, holidays, sports event periods, maximum temperature, and precipitation were found to have significant impacts on beer sales volume. Sales volume increased by approximately 117.66 thousand liters on holidays and by about 148.87 thousand liters during sports events. Regarding weather factors, a 1°C increase in maximum temperature led to an average sales increase of approximately 15.49 thousand liters, while a 1mm increase in precipitation resulted in an average sales decrease of about 5.41 thousand liters. This suggests that Pilsner sales tend to increase with higher temperatures and decrease with more precipitation.

For Pale Lager, holidays, sports event periods, maximum temperature, and precipitation were also found to have significant impacts on sales volume. Sales volume increased by approximately 834.32 thousand liters on holidays and by about 1381.40 thousand liters during sports events. In terms of weather factors, a 1°C increase in maximum temperature led to an average sales increase of approximately 163.04 thousand liters, while a 1mm increase in precipitation resulted in an average sales decrease of about 41.75 thousand liters. This indicates that Pale Lager sales also tend to increase with higher temperatures and decrease with more precipitation. The ARIMA model's lag terms included the second-order autoregressive term (L2.ar, 0.738) and the first-order moving average term (L1.ma, -0.483), both of which were significant. The second-order autoregressive term (L2.ar) with a coefficient of 0.738 indicates that sales volumes from two lags prior positively impact the current sales volume. In contrast, the first-order moving average term (L1.ma) with a coefficient of -0.483 indicates that the forecast error from the previous time point negatively impacts the current sales volume.

For Amber Lager, holidays, sports event periods, and maximum temperature did not have significant impacts on beer sales volume, but precipitation and humidity did. A 1mm increase in precipitation resulted in an average sales decrease of approximately 0.18 thousand liters. When humidity increased by 1% rh, sales volume increased by approximately 0.17 thousand liters. The ARIMA model's lag terms included the first-order autoregressive term (L1.ar, 0.526) and the first-order moving average term (L1.ma, 0.358), both of which were significant. This indicates that both the sales volume from the previous time point and the forecast error from the previous time point positively impact the current sales volume.

Table 3: Analysis Results

	Pilsner	**Pale**	**Amber**
	(2,0,1)	**(2,0,3)**	**(1,0,1)**
holiday	11.766*** (2.753)	83.432*** (20.129)	0.161 (0.142)
sport	14.887*** (3.898)	138.140*** (38.249)	-0.041 (0.511)
temperature	1.549*** (0.397)	16.304*** (2.813)	0.002 (0.013)
rain	-0.541** (0.251)	-4.175* (2.276)	-0.018* (0.01)
humid	0.087 (0.183)	-0.869 (1.968)	0.017** (0.007)
sun	0.054 (0.329)	1.057 (3.389)	0.014 (0.014)
_cons	120.565*** (16.09)	954.834*** (125.888)	-0.359 (0.576)
L1.ar	0.460** (0.188)	-0.012 (0.136)	0.526*** (0.143)
L2.ar	0.423*** (0.15)	0.738*** (0.156)	
L1.ma	-0.181 (0.216)	-0.483* (0.256)	0.358* (0.186)

	Pilsner	Pale	Amber
	(2,0,1)	(2,0,3)	(1,0,1)
L2.ma		0.38 (76.895)	
L3.ma		-0.62 (47.679)	
AIC	814.0311	1274.044	119.959
BIC	843.1194	1303.133	146.402
vif		1.6	

Note: ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

5.2.2. Ale

For Wheat beer, holidays, sports event periods, and maximum temperature were found to have significant impacts on sales volume. Sales volume increased by approximately 58.24 thousand liters during holidays and by about 63.36 thousand liters during sports events. Regarding weather factors, a 1°C increase in maximum temperature led to an average sales increase of approximately 8.53 thousand liters, suggesting that Wheat beer sales tend to increase with higher temperatures. The second-order autoregressive term (L2.ar, 0.461) in the ARIMA model was found to be significant.

For Stout, holidays, sports event periods, maximum temperature, and precipitation were found to have significant impacts on sales volume. Sales volume increased by approximately 16.17 thousand liters during holidays and by about 21.84 thousand liters during sports events. In terms of weather factors, a 1°C increase in maximum temperature led to an average sales increase of approximately 1.06 thousand liters, while a 1mm increase in precipitation resulted in an average sales decrease of about 0.67 thousand liters. This suggests that Stout sales tend to increase with higher temperatures and decrease with more precipitation. The first-order autoregressive term (L1.ar, 0.955) and the first-order moving average term (L1.ma, -0.453) in the ARIMA model were found to be significant.

For Belgian Ale, holidays were found to have a significant impact on sales volume, with sales volume increasing by approximately 3.01 thousand liters during holidays. Regarding weather factors, maximum temperature, precipitation, and sunshine duration did not have significant impacts on sales volume. The first-order autoregressive term (L1.ar, 0.925) and the fourth-order moving average term (L4.ma, 0.289) in the ARIMA model were found to be significant. The impact of humidity on all Ale sales aligns with the findings of Kim (2012), which indicated that relative humidity and sunshine duration do not significantly affect beer sales. On the other hand, Jung et al. (2023) study suggested that higher humidity leads to increased beer sales, indicating that the effect of humidity on beer consumption may vary by beer type.

Table 4: Analysis Results

	Wheat	Stout	Belgian
	(2,0,1)	(1,0,1)	(1,0,4
holiday	5.824*** (1.24)	1.617*** (0.343)	0.301*** (0.113)
sport	6.336*** (1.8)	2.184*** (0.767)	0.224 (0.153)
temperature	0.853*** (0.14)	0.106** (0.502)	0.02 (0.020)
rain	-0.148 (0.13)	-0.067** (0.027)	-0.014 (0.011)
humid	0.005 (0.09)	0.002 (0.026)	0.009 (0.010)
sun	0.071 (0.14)	0.01 (0.041)	0.02 (0.013)
_cons	59.044*** (5.55)	19.156*** (2.321)	0.853 (0.789)
L1.ar	0.239** (0.22)	0.955*** (0.037)	0.925*** (0.047)
L2.ar	0.461*** (0.13)		
L1.ma	0.003 (0.24)	-0.453*** (0.098)	-0.161 (0.105)
L2.ma			0.065 (0.123)
L3.ma			-0.157 (0.124)
L4.ma			0.289*** (0.14)
AIC	647.9564	387.6926	125.7413
BIC	677.0447	414.1365	160.1184
vif		1.6	

Note: ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

5.2.3. Model Diagnostics and Forecasting

To verify whether the estimated model fits the observed time series well, model diagnostics were performed, primarily using residual analysis. After deriving the results, the Box-Ljung statistics were reviewed to check the stability of the residuals (Appendix 3). The results indicated that for all beer items, the null hypothesis that the residuals are white noise, i.e., stable, could not be rejected. This study aims to verify how various climate factors and specific periods affect the consumption patterns of each type of beer by predicting sales volumes based on past beer sales data.

Using the final ARIMAX model established through several procedures, an analysis was attempted with weekly seasonal variables and exogenous variables such as sports event periods from January 2018 to December 2019. A total of 104 weeks of data were used as training data to fit the model. The remaining 31 weeks of data from January 1, 2020, to the first week of August 2020, were used as test data to evaluate the model's performance. The results of predicting beer sales volumes over the 31-week period in 2020 based on the training data are shown in Figure 1-6. The blue line represents the observed values, while the red line represents the predicted values from the model.

For Pilsner, the actual sales volumes and the model's predicted values show a generally similar pattern. The model captures the increasing trends and fluctuations in sales volumes well, and the predicted values are considered similar to the actual values.

For Pale Lager, the actual sales volumes and predicted values mostly align, although there are some periods where the predictions do not fully match the observed values. Despite this, the overall sales trend is well reflected.

For Amber Lager, the actual sales volumes show a decreasing trend over time, and the model's predicted values also reflect this decreasing trend.

For Wheat Beer, the actual sales volumes and the model's predicted values show a generally similar pattern. The model accurately captures the increasing sales volumes and significant fluctuations.

For Belgian Ale, the actual sales volumes and predicted values mostly match, reflecting the increasing sales trend well. There are some periods with differences between the predicted and observed values, but the prediction model generally follows the trend well.

For Stout, the actual sales volumes show an increasing trend over time, and the model's predicted values reflect this increasing trend well. The significant fluctuations are also similarly reflected in both the predictions and the actual values.

Overall, across all beer types, the actual sales volumes were relatively higher than the predicted values. This discrepancy is likely due to the increased frequency at-home drinking during the 31-week period in 2020 because of the COVID-19-related stay-at-home measures (Ministry of Food and Drug Safety, 2020; Korea Agro-Fisheries & Food Trade Corporation, 2021). Although there are differences between the predicted and actual sales volumes, the increasing trend in sales volumes and significant fluctuations showed similar patterns.

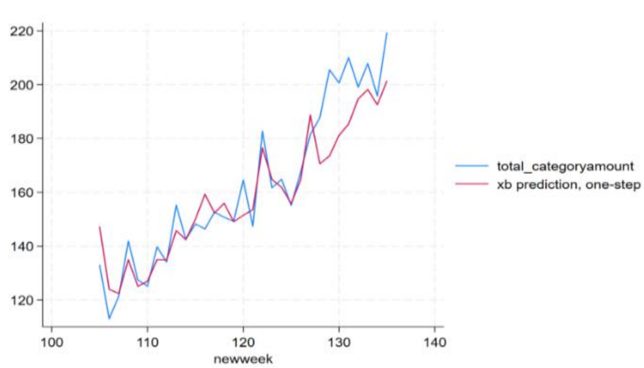

Figure 1: Plisner

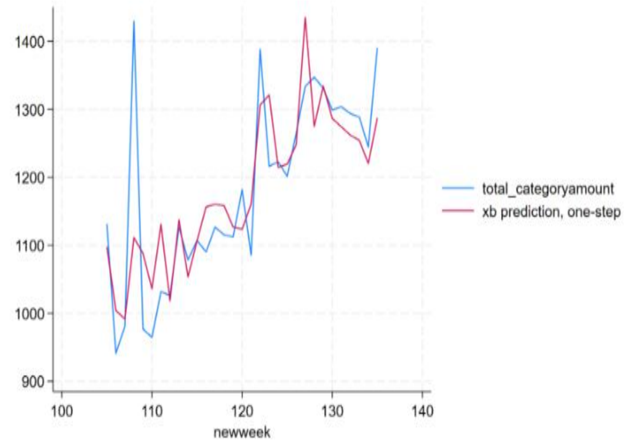

Figure 2: Pale Lager

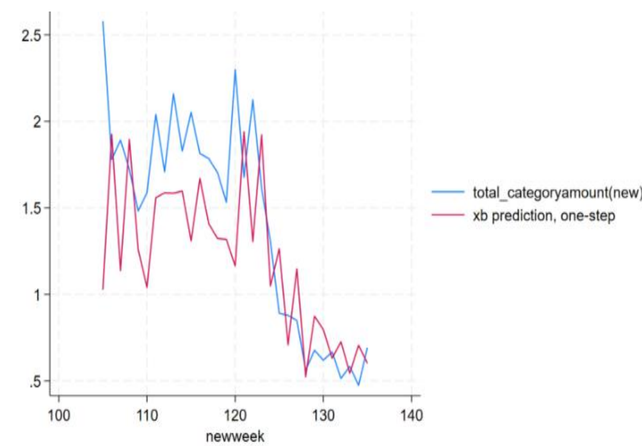

Figure 3: Amber Lager

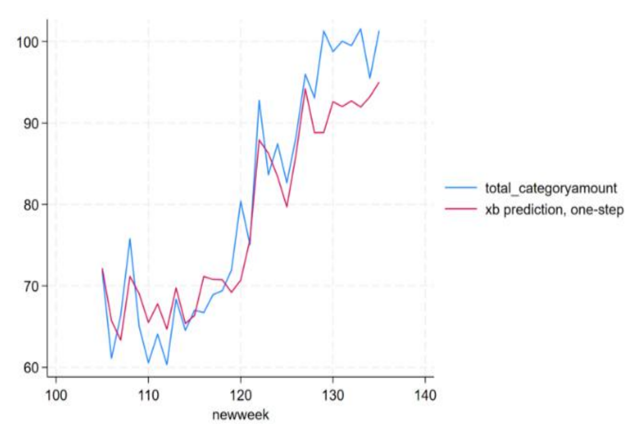

Figure 4: Wheat Beer

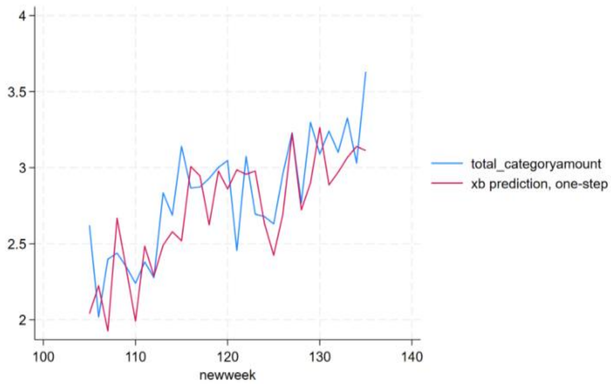

Figure 5: Belgium Ale

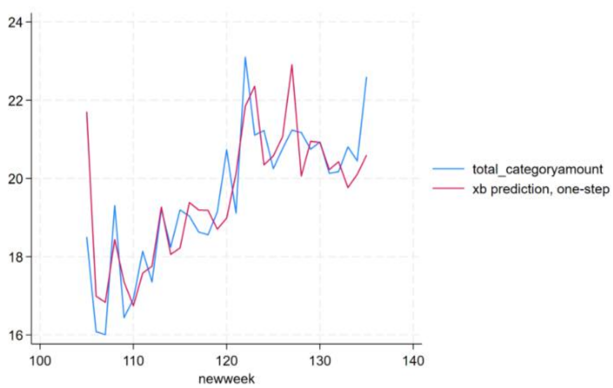

Figure 6: Stout

The predictive power verification results of the ARMAX model showed that the RMSPE was approximately within a 10% error range, indicating satisfactory predictive accuracy (Table 5). Theil's U inequality coefficient was also found to be roughly below 0.1, suggesting no issues with the model's predictive capabilities. However, for some items, the predictive power was relatively lower.

Table 5: Predictive Testing of Estimates

Type		Model	RMSPE	Theil's U
Lager	Plisner	ARMAX (2,0,1)	0.59%	0.032
	Pale Lager	ARMAX (2,0,3)	0.63%	0.033
	Amber Lager	ARMAX (1,0,1)	6.88%	0.174
Ale	Wheat beer	ARMAX (2,0,1)	0.59%	0.031
	Stout	ARMAX (1,0,1)	0.53%	0.026
	Belgium Ale	ARMAX (1,0,4)	1.03%	0.051

Note: Theil's U inequality coefficient ranges between 0 and 1, with values closer to 0 indicating higher model predictive accuracy, Lower RMSPE values indicate smaller prediction errors and better predictive performance of the model.

5.3. Multiple Regression Analysis

5.3.1 Lager

For Pilsner and Pale Lager, holidays, sports event periods, and daily maximum temperature were found to have positive impacts on beer sales volumes, with sports events having the largest estimated impact. These results are similar to those of the ARMAX model. However, in the multiple regression model, precipitation was not found to have a significant impact on the overall sales volume of Lagers, showing a difference from the ARMAX model, which indicated that precipitation significantly affected overall Lager sales.

For Amber Lager, both the multiple regression model and the ARMAX model showed that changes in humidity had a positive impact on sales. In the case of Pilsner, humidity significantly impacted sales volume in the multiple regression model, but not in the ARMAX model.

Table 6: Analysis Results

	Pilsner	Pale	Amber
holiday	9.137** (3.738)	89.554*** (30.293)	0.203 (0.143)
sport	22.252*** (6.744)	217.805*** (48.798)	-0.023 (0.230)
temperature	2.006*** (0.244)	15.792*** (1.747)	-0.012 (0.008)
rain	0.048 (0.412)	-2.746 (2.988)	0.004 (0.014)
humid	-0.433* (0.233)	-0.376 (1.836)	0.015* (0.009)
sun	0.572 (0.517)	3.985 (3.726)	0.019 (0.018)
_cons	143.422*** (15.116)	898.161*** (108.731)	-0.186 (0.513)
N	104	104	104
Adjusted R^2	0.5283	0.6178	0.0003

Note: ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

5.3.2 Ale

For Wheat beer, holidays, sports event periods, and daily maximum temperature were found to have positive impacts on beer sales volumes, and these results are similar to those of the ARMAX model. However, precipitation did not have a significant impact on Wheat beer sales volumes in either the multiple regression model or the ARMAX model.

For Stout, holidays, sports event periods, and daily maximum temperature significantly impacted sales volumes in both models. However, while precipitation had a significant impact in the ARMAX model, it was not significant in the multiple regression model.

For Belgian Ale, daily maximum temperature had a significant impact only in the multiple regression model and not in the ARMAX model. Humidity significantly impacted Belgian Ale sales volumes in the multiple regression model, but not in the ARMAX model.

Table 7: Analysis Results

	Wheat	Stout	Belgian
holiday	6.244*** (1.598)	1.538** (0.619)	0.388 (0.247)
sport	9.940*** (2.573)	4.711*** (0.994)	-0.584 (0.398)
temperature	0.825*** (0.093)	0.088** (0.036)	0.027** (0.014)
rain	-0.109 (0.158)	-0.009 (0.061)	-0.026 (0.024)
humid	0.103 (0.097)	-0.013 (0.038)	0.043*** (0.015)
sun	0.22 (0.197)	0.06 (0.075)	0.026 (0.003)
_cons	52.39*** (5.748)	19.567*** (2.2269)	-1.384 (0.889)
N	104	104	104
Adjusted R^2	0.6597	0.2403	0.2654

Note: ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

In this study, the ARMAX model and the multiple regression model were compared to evaluate the beer sales volume prediction performance using RMSPE and Theil's U values. The analysis results showed that the ARMAX model generally had lower RMSPE and Theil's U values compared to the multiple regression model. This indicates that the ARMAX model has higher predictive accuracy by effectively capturing the characteristics of time series data. Therefore, the ARMAX model demonstrated superior prediction performance over the multiple regression model.

Table 8: Predictive Testing of Estimates

Type		RMSPE	Theil's U
Lager	Pilsner	0.59%	0.032
	Pale	0.63%	0.033
	Amber	6.88%	0.174
Ale	Wheat	0.59%	0.031
	Stout	0.53%	0.026
	Belgian	1.03%	0.051

Note: Theil's U inequality coefficient ranges between 0 and 1, with values closer to 0 indicating higher model predictive accuracy, Lower RMSPE values indicate smaller prediction errors and better predictive performance of the model.

5.2.4. Marketing Strategy Based on Analysis Results

Based on the estimation of the time series analysis model and the analysis of the characteristics of each beer type, the following marketing strategies can be suggested. For Lagers such as Pilsner and Pale Lager, and Ales such as Wheat Beer and Stout, sales volumes tend to increase with rising temperatures. This suggests the need to secure sufficient inventory of these beers during high-temperature seasons like summer. From a promotional perspective, introducing limited edition summer packages to attract consumer interest and organizing tasting events or giveaways linked to major summer events (e.g., music festivals, beach parties) can encourage consumer participation. Lagers such as Pilsner, Pale Lager, Amber Lager, and Ales like Stout tend to see a decrease in sales volumes with increased precipitation.

Therefore, it may be beneficial to adjust the inventory of these beers during rainy seasons or monsoon periods to reduce costs. Conducting limited-time discount events on humid days and ensuring sufficient inventory of Amber Lager during this period is recommended. Additionally, utilizing social media to post marketing content tailored to humidity can effectively drive consumption. During holidays, sales volumes of Lagers such as Pilsner and Pale Lager, and Ales like Wheat Beer, Stout, and Belgian Ale significantly increase. Planning special discount events or promotions during this period can be an opportunity to boost sales.

Moreover, since sales volumes of Wheat Beer, Stout, Pilsner, and Pale Lager significantly increase during sports event periods, it is essential to strengthen marketing campaigns aligned with major sports events (e.g., soccer and baseball games, the Olympics). These strategies are based on the analysis of how various factors affect beer consumption patterns and should be adjusted flexibly according to the timing and situation of their application.

6. Conclusions

This study analyzed the impact of weather factors, holidays, and sports events on beer consumption using multiple regression analysis and the ARMAX model. The model verification results indicated that the ARMAX model had better predictive performance than the multiple regression model. Through time series analysis, this study confirmed how each variable affects beer consumption patterns. The analysis results showed that temperature increases positively impacted most beer sales, while precipitation increases tended to decrease sales. Sales of Pilsner and Pale Lager increased with rising temperatures, but overall, Lager sales decreased with increased precipitation. This reflects a trend where Lager consumption rises during hot summer weather and decreases on rainy days.

In contrast, among Ales, only Stout sales decreased with increased precipitation, indicating that precipitation has a greater impact on Lagers than on Ales. Among weather factors, sunshine duration did not significantly affect beer sales, while humidity only impacted Amber Lager. These results demonstrate variations in findings across previous studies.

Based on the analysis results, marketing strategies were suggested, which should be adjusted flexibly according to the application timing and situation based on how each variable influences beer consumption patterns.

The limitations of this study are as follows. First, the prediction results across all beer items showed that actual beer sales were relatively higher than the predicted values. This discrepancy is likely due to the increase in at-home drinking frequency during the COVID-19 pandemic, as stay-at-home measures were implemented during the period. Therefore, the inability to reflect special situations like the pandemic in beer consumption patterns explains the differences between predictions and actual results. Future research should develop prediction models that more precisely consider such external factors to derive more accurate forecasts. Second, this study used weekly data for analysis, treating all days in a week that included holidays and sports events equally.

Consequently, there may be limitations in generalizing results for weeks that mix holidays and weekdays. It would be more desirable to use daily statistical data for predictions to derive more accurate results. Despite these limitations, this study is significant in exploring the influence of environmental factors like weather on beer purchasing behavior in Korea, where such research is limited. This study is distinguished from previous research by dividing beer into Lagers and Ales and further categorizing them for a detailed analysis. Emphasizing that the results provide useful information for breweries, beer processing companies, and retailers in planning store operations and inventory according to weather trends, this study is expected to serve as a reference for forecasting beer demand.

References

Agnew, M. D., & Palutikof, J. P. (1999). "The impacts of climate on retailing in the UK with particular reference to the anomalously hot summer of 1995". *International Journal of Climatology: A Journal of the Royal Meteorological Society, 19(13),* 1493-1507.

Bratina, D., & Faganel, A. (2008). "Forecasting the primary demand for a beer brand using time series analysis". *Organizacija, 41(3),* 116-124.

Cao, M., & Wei, J. (2005). "Stock market returns: A note on temperature anomaly". Journal of Banking & Finance, 29(6), 1559-1573

Cho, H. (2018). Comparison of beer consumption motives by consumption level: Focusing on female consumers in their 20s. Journal of Foodservice Management, 21(5), 141-168.

CNBC "Super Bowl Billions: The Big Business Behind the Biggest Game of the Year" ,2017,1.23

Hirche, M., Haensch, J., & Lockshin, L. (2021). "Comparing the day temperature and holiday effects on retail sales of alcoholic beverages–a time-series analysis". International Journal of Wine Business Research, 33(3), 432-455.

Hong, J., Lee, H., & Na, J. (2012). The effect of weather factors on seasonal product sales in discount stores. Journal of Distribution Management, 15(6), 5-19.

Jung, H., Kim, K., Cho, M., Lee, C., & Lee, Y. (2023). Consumption status of alcoholic beverages by day, season, and weather - focusing on traditional liquor, wine, spirits, soju, and beer. Journal of the East Asian Society of Dietary Life, 33(5), 434-442.

Kim, C., Seo, H., Lee, H., & Kim, J. (2018). Establishing a Hanwoo supply and demand model using beef traceability data. Journal of Rural Economics, 41(3), 25-50.

Kim, H., & Cho, S. (2007). The effect of consumer lifestyle on beer selection attributes. Journal of Tourism and Leisure Research, 19(3), 187-204.

Kim, S. (2012). Analysis of the impact of weather and macroeconomic variables on the liquor industry. Industrial Economic Review, 25(1), 217-239.

King, C., & Narayandas, D. (2000). "Coca-Cola's New Vending Machine (A): Pricing to Capture Value, or Not?". Harvard Business School.

Knez, I., Thorsson, S., Eliasson, I., & Lindberg, F. (2009). "Psychological mechanisms in outdoor place and weather assessment: towards a conceptual model". International journal of biometeorology, 53, 101-111.

Korea Agro-Fisheries & Food Trade Corporation. (2021). Liquor market trend report.

Korea Consumer Agency. (2018). Investigation of prices and distribution status of imported processed foods.

Kwak, H. J., Kim, S. K., Lee, B. S., Li, X. H., & Lee, J. H. (2018). Analysis of purine content in beer according to fermentation temperature. Korean Journal of Microbiology, 54(4), 379-383.

Lee, K., Kim, S., & Kim, T. (2018). The effect of weather on consumers' purchase of agricultural products. Journal of Distribution Management, 21(4), 137-147.

Lenten, L. J., & Moosa, I. A. (1999). "Modelling the trend and seasonality in the consumption of alcoholic beverages in the United Kingdom". Applied Economics, 31(7), 795-804.

Li, C., Luo, X., Zhang, C., & Wang, X. (2017). "Sunny, rainy, and cloudy with a chance of mobile promotion effectiveness". Marketing Science, 36(5), 762-779.

Meese, R. A., & Rogoff, K. (1983). "Empirical exchange rate models of the seventies: Do they fit out of sample?". Journal of international economics, 14(1-2), 3-24.

Murray, K. B., Di Muro, F., Finn, A., & Leszczyc, P. P. (2010). "The effect of weather on consumer spending. Journal of Retailing and Consumer Services", 17(6), 512-520.

Olson, K. L., Whitley, P., Velasco, J., LaRue, L., Dawson, E., & Huskey, A. (2021). "Seasonal and regional influences on alcohol consumption: an analysis of near-real-time urine drug test results in those seeking health care". Drug and alcohol dependence, 227, 108908.

Park, J., Lee, S., Choi, I., Choi, H., Kim, N., Shin, D., ... & Oh, S. (2019). Quality characteristics of rice wort and rice beer according to rice processing. Journal of the Korean Society of Industrial Food Science and Technology, 23(4), 290-296.

Parsons, A. G. (2001). "The association between daily weather and daily shopping patterns". Australasian Marketing Journal (AMJ), 9(2), 78-84.

Puljula, J., Savola, O., Tuomivaara, V., Pribula, J., & Hillbom, M. (2007). "Weekday distribution of head traumas in patients admitted to the emergency department of a city hospital: effects of age, gender and drinking pattern". Alcohol & Alcoholism, 42(5), 474-479.

Roslow, S., Li, T., Nicholls, J.A.F., 2000. "Impact of situational variables and demographic attributes in two seasons on purchase behavior". European Journal of Marketing 34 (9/10), 1167–1180.

Rosman, K. (2013). "Weather Channel now also forecasts what you'll buy". The Wall Street Journal, 14(August)

Statista "French people declaring an increase in their consumption of aperitifs, beer and pizza during the Football World Cup in 2018", 2021,7.5

Talking Retail "62 million more pints of beer could be sold during World Cup" , 2022,10.20

Tian, X., Cao, S., & Song, Y. (2021). "The impact of weather on consumer behavior and retail performance: Evidence from a convenience store chain in China". *Journal of Retailing and Consumer Services, 62*, 102583.

Yoo, S., Sung, H., & Ko, J. (2015). A study on beer selection attributes using conjoint analysis. *Journal of Tourism and Leisure Research, 27(7)*, 341-360.

Appendixes

Appendix 1: Holiday and Sports Event Variables

Year	Event	Date	Week Number	Week
2018	New Year	January 1	201801	1
	Winter Olympics	February 9 - February 25	201806	6
			201807	7
			201808	8
	Independence Movement Day	March 1	201809	9
	Children's Day	May 5	201818	18
	Buddha's Birthday	May 22	201821	21
	Memorial Day	June 6	201823	23
	World Cup	June 14 - July 15	201824	24
			201825	25
			201826	26
			201827	27
	Liberation Day	August 15	201833	33
	Chuseok	September 24	201839	39
	National Foundation Day	October 3	201840	40
	Hangul Day	October 9	201841	41
	Christmas	December 25	201852	52
2019	New Year	January 1	201901	53
	Lunar New Year	February 4	201906	58
	Independence Movement Day	March 1	201909	61
	Children's Day	May 5	201918	70
	Buddha's Birthday	May 12	201919	71
	Memorial Day	June 6	201923	75
	Liberation Day	August 15	201933	85
	Chuseok	September 12	201937	89
	National Foundation Day	October 3	201940	92
	Hangul Day	October 9	201941	93
	Christmas	December 25	201952	104
2020	New Year	January 1	202001	105
	Lunar New Year	January 24	202004	108
	Independence Movement Day	March 1	202009	113
	Buddha's Birthday	April 30	202018	122
	Children's Day	May 5	202019	123
	Memorial Day	June 6	202023	127

Appendix 2: Stationarity and Seasonality Test Results

	ADF Statistic	
	Raw Series	Differenced series
Wheat	-3.538***	-
Belgian	-2.635***	-
Stout	-0.429***	-
Pilsner	-3.333**	-
Pale	-4.868***	-
Amber	-4.115***	-

Note: ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Appendix 3: Residual Test using Box-Ljung Statistic

Type		Q- statistic	Prob
Lager	Pilsner	45.6245	0.2497
	Pale	32.8762	0.7804
	Amber	15.8517	0.9998
Ale	Wheat	55.3697	0.0537
	Stout	44.0356	0.3047
	Belgian	45.8983	0.2409