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Modeling and Forecasting Monthly Domestic Tourism Expenditure through the SARIMAX Approach

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Abstract

Forecasting domestic tourism expenditure supports budgeting, financial planning, and encourages responsible spending, fostering economic stability. The Consumer Price Index (CPI) is crucial for domestic tourism expenditure as it reflects inflation, guiding budget decisions and expenditure planning. However, there is limited research that focuses on predicting monthly domestic tourism expenditure. This paper proposes a forecasting framework that employs a seasonal autoregressive integrated moving average model with exogenous variables (Consumer Price Index (CPI)) to forecast domestic tourism expenditure. The dataset of this study contains monthly observations from the Korea Tourism Knowledge & Information System and a set of exogenous variables such as monthly Consumer Price Index (CPI) data for Transportation, Recreation and Culture, and Restaurants and Hotels. Experimental results indicated that SARIMAX model shows a predictive accuracy.

Keywords: domestic tourism expenditure; consumer price index; SARIMAX model; econometrics

1. Introduction

Along with the significant growth in tourism, tourism expenditure in South Korea has also increased significantly (Statista Research Department, 2024). In the third quarter of 2023, the domestic tourism expenditure in South Korea amounted to 10.2 trillion won, indicating a 1.2% increase compared to the third quarter of 2022 (Tourism Knowledge & Information System, 2024). The role of tourism is pivotal in the attainment of sustainable growth (Balciar et al., 2024). One of the biggest challenges facing the tourism today is the need to overcome the lack of information/knowledge necessary to target real consumers and seek out what they actually need (Jang & Ham, 2009). Understanding tourism expenditure is crucial because tourism relies on spending, and a clear grasp aids in targeting market segments and shaping effective tourism industry strategies (Lin et al., 2015).

The Consumer Price Index (CPI) is a vital macroeconomic gauge that mirrors the changes in the prices of goods and services (Zhang et al., 2023). The CPI attempts to measure the average cost of living in a given country by estimating the purchasing power of a single unit of currency (Barkan et al., 2023). Consequently, it serves as the primary macroeconomic indicator for gauging inflationary or deflationary trends and plays a pivotal role in shaping various market dynamics within the economy. In South Korea, the top CPI headline is composed of eight major sector indexes: food and non-alcoholic beverages, alcoholic beverages and electricity, gas, and other fuels, furnishings, household equipment & routine maintenance, health, transport, communication, recreation and culture, education, restaurants and hotels, and other goods and services (Statistics Korea, 2024).

Despite the growing body of research on tourism demand forecasting, most existing studies have predominantly concentrated on forecasting tourist arrivals rather than tourism expenditure, often at an aggregated level without incorporating key economic determinants (Ognjanov et al., 2018). However, tourism expenditure provides a more direct reflection of the economic contribution of tourism activities and thus offers a more comprehensive measure for policy and strategic planning.

Furthermore, while the Consumer Price Index (CPI) is a critical macroeconomic indicator that influences consumer behavior and purchasing power, limited studies have integrated CPI—especially its sector-specific components such as Transportation, Recreation and Culture, and Restaurants and Hotels—into tourism expenditure forecasting models.

This study addresses this research gap by developing a Seasonal Autoregressive Integrated Moving Average model with Exogenous variables (SARIMAX) that integrates CPI sub-indices as external predictors. By doing so, it not only enhances the accuracy of expenditure forecasting but also provides new insights into how inflationary pressures in key consumption sectors shape domestic tourism spending patterns in South Korea. This integrative framework represents a novel empirical contribution to both tourism economics and applied forecasting research. This paper proposes a forecasting framework that employs a seasonal autoregressive integrated moving average model with exogenous variables (Consumer Price Index (CPI)) to forecast domestic tourism expenditure. Time-series models use historical tourism expenditure observations $y_{t-1}, y_{t-2}, \dots, y_{t-p}$ as inputs to predict the future tourism expenditure (Cang & Hemmington, 2010).

However, historical tourism expenditure observations $y_{t-1}, y_{t-2}, \dots, y_{t-p}$ and the diverse factors that affect tourism expenditure can both be used as inputs for econometric models. These diverse factors are Consumer Price Index (CPI) data for Transportation, Recreation and Culture, and Restaurants and Hotels.

2. Literature review

2.1. Domestic tourism expenditure

Tourism has undergone sustained growth and extensive diversification over the decades, emerging as one of the world's fastest-growing economic sectors, with its business volume now comparable to or even surpassing that of oil exports, food products, or automobiles (UNWTO, 2024). The country's domestic tourism industry has flourished in recent years, and its tourism expenditure and domestic tourism volume has made considerable contributions to the country's national and regional economic growth (Wei et al., 2018). The total domestic tourism volume represents four key indicators of the

travel behavior of South Korean citizens, quantified as travel experience rate, frequency of travel, duration of travel, and domestic travel expenditure (Tourism Knowledge & Information System, 2024). According to the results of the National Travel Survey for the third quarter of 2023 that published by Ministry of Culture, Sports and Tourism (2024) the domestic tourism expenditure of South Korea in the third quarter of 2023 was 10.2 trillion won, marking a 1.2% increase from the third quarter of 2022.

Little research has been conducted on forecasting tourism expenditure at the national level, as the majority of tourism forecasting studies have focused primarily on aggregated tourist arrivals rather than actual expenditure patterns (Ognjanov et al., 2018). Ognjanov et al. (2018) examined the use of tourism expenditure data to evaluate the economic impacts of tourism across regional areas in China, highlighting the managerial usefulness of expenditure-based forecasting for understanding regional economic growth dynamics. Similarly, Georgantopoulos (2012) projected tourism expenditure trends for 2012–2020, identifying a continuous rise in total expenditure and a particularly strong increase in business travel spending, suggesting the sensitivity of different market segments to macroeconomic conditions. In the earlier work by Cang and Hemmington (2010), the authors investigated U.K. inbound tourism expenditure disaggregated by purpose of visit, utilizing the ARIMA model to demonstrate its robustness and applicability for short-term forecasting. Despite these contributions, a systematic integration of macroeconomic variables, such as the Consumer Price Index (CPI), into expenditure forecasting models remains limited. Most existing studies have emphasized methodological accuracy rather than examining the economic determinants that shape tourism expenditure behavior. Hence, the current research seeks to bridge this gap by developing a forecasting framework that not only applies advanced time-series modeling (SARIMAX) but also incorporates CPI sub-indices—such as Transportation, Recreation and Culture, and Restaurants and Hotels—to capture inflation-driven expenditure dynamics within South Korea's tourism sector.

2.2. *Consumer Price Index*

The Consumer Price Index (CPI) is a statistic compiled to track the changes in prices of goods and services that households acquire for their daily living (Korean Statistical

Information Service, 2024). The Consumer Price Index (CPI) is utilized as fundamental data by the government for economic assessments, and it is also employed in various contexts such as adjusting pension disbursements by the National Pension Service, taking into account changes in purchasing power. The Consumer Price Index thus impacts the government, businesses, and overall aspects of citizens' lives. Over the past decades, several studies have been devoted to exploring the characteristics and determinants of tourism expenditure using a broad range of theoretical and methodological approaches (Wei et al., 2018). Several previous studies have investigated the determinants of tourism expenditure, including demographics, trip-related features. Bernini and Cracolici (2015) analyzed how demographic changes in the population affect tourism decision-making process along an individual's life cycle. Trip-related characteristics, namely accommodation, activities, destination, travel information source, length of stay, all have an impact on tourism expenditure (Aguilo et al., 2017). Although the studies on determinants of tourism expenditure are abundant, most of them have neglected the discussions on the relationships between CPI and domestic tourism expenditure. The CPI is crucial for domestic tourism expenditure as it reflects inflation, guiding budgeting decisions and expenditure planning. Therefore, it is worthwhile to employs a seasonal autoregressive integrated moving average model with exogenous variables Consumer Price Index to forecast domestic tourism expenditure. This research makes a significant contribution to the literature in domestic tourism expenditure forecasting at national. Forecasts of domestic tourism expenditure may be of greater importance than forecasts of domestic tourism arrivals when assessing the economic impacts of tourism. At the national level there can be wide variations in the concentration of different source markets that can lead to varying lengths of stay, and differing levels of expenditure. The research provides practical management outcomes by providing methods for forecasting domestic tourism expenditure as an indicator of economic in South Korea. The research concludes with the findings on the most appropriate model for national forecasting and potential new variables suitable at the national level.

3. Methodology

3.1. Data

This study utilized the monthly data of domestic tourism expenditure obtained from the Korea Tourism Knowledge & Information System (<https://knowtour.go.kr>). The monthly Consumer Price Index (CPI) data for Transportation, Recreation and Culture, and Restaurants and Hotels in South Korea were used as X variables and obtained from the Statistics Korea website (<https://kostat.go.kr>) and are presented in Figure 1 summarized in Table 1.

To ensure robust model evaluation, the dataset was divided into two subsets: Training set (80%): January 2018 – December 2022 (54 observations). Testing set (20%): January 2023 – August 2023 (14 observations). The training set was used for model fitting and parameter optimization, while the testing set was reserved exclusively for out-of-sample validation by Eviews.

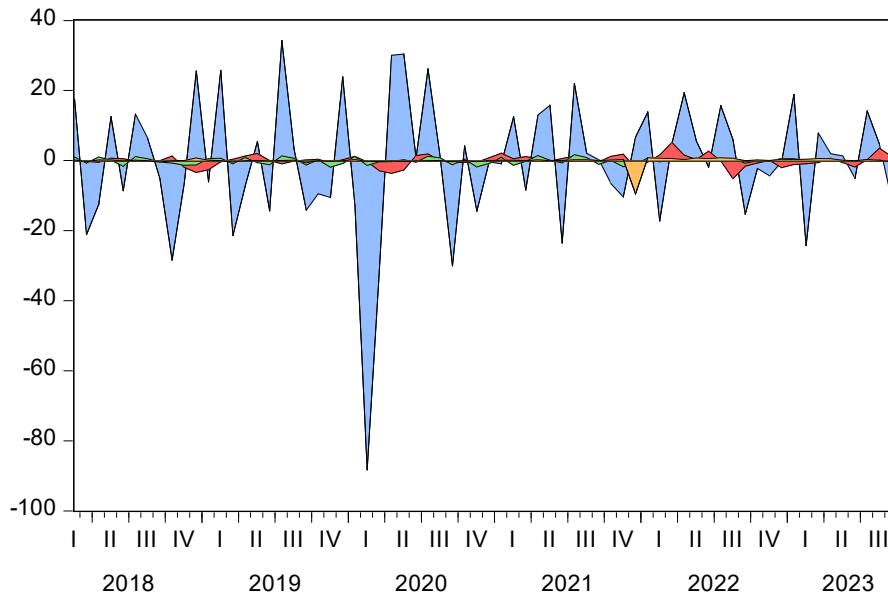


Figure 1. Time-serial on monthly data.

Table 1. Summarization of four variables.

	EXPENDITURE	TRANSPORTATION	RECREATION	RESTAURANT
Mean	-0.231472	0.174067	0.079924	0.151625
Median	0.628507	0.241479	0.169574	0.231351
Maximum	34.38318	5.365003	1.850545	0.982654
Minimum	-88.08581	-5.008729	-1.665889	-9.378898
Std. Dev.	18.83675	1.650333	0.868766	1.212429
Skewness	-1.352027	-0.224851	-0.183461	-7.274004
Kurtosis	8.324416	4.725719	2.225561	57.85719
Jarque-Bera	101.0404	9.010963	2.080767	9126.041
Probability	0.000000	0.011048	0.353319	0.000000
Sum	-15.74013	11.83655	5.434813	10.31051
Sum Sq.				
Dev.	23773.16	182.4812	50.56855	98.48887
Observations	68	68	68	68

The consumer price index is estimated using the Laspeyres formula, and the formula is as follows (Lee et al., 2021).

$$P_L = \frac{\sum(P_i^t Q_i^o)}{\sum(P_i^o Q_i^o)} = \sum S_i^o (P_i^t / P_i^o) \quad (1)$$

$$S_i^o = \frac{P_i^o Q_i^o}{\sum(P_i^o Q_i^o)} \quad (2)$$

P represents price, Q represents quantity, S represents weight, O represents the base period, t represents the comparison period, and i represents the item.

3.2. Method

Seasonal ARIMAX is an advancement of the seasonal ARIMA with external feature variables (X) called SARIMAX (p, d, q) * (P, D, Q) , to improve its prediction and performance(Manigandan et al., 2021). The seasonal ARIMAX model can be suggested as follows.

$$\varphi_p(G)\phi_p(G^{seasonal})(1 - G)^D X_t = \alpha_k y_{k,t} + Y_q(G)w_Q(G^{seasonal})e_t \quad (3)$$

where $y_{k,t}$ are the corresponding observations of the k^{th} represented as the number of exogenous variables at the time t , and α_k represents the correlation coefficient value of the k^{th} exogenous (X) input variables.

3.3. Analysis and Measures of Performance

To evaluate, the measure used to forecast the models in this study is the root mean square error (RMSE) and mean absolute percentage error (MAPE) (Manigandan et al., 2021) shown in Equations (4) and (5), given below

$$MAPE\% = \frac{\sum_{t=1}^n \frac{|E_t - F_t|}{E_t}}{n} \quad (4)$$

$$RMSE = \sqrt{\frac{1}{n} \sum_{t=1}^n (E_t - F_t)^2} \quad (5)$$

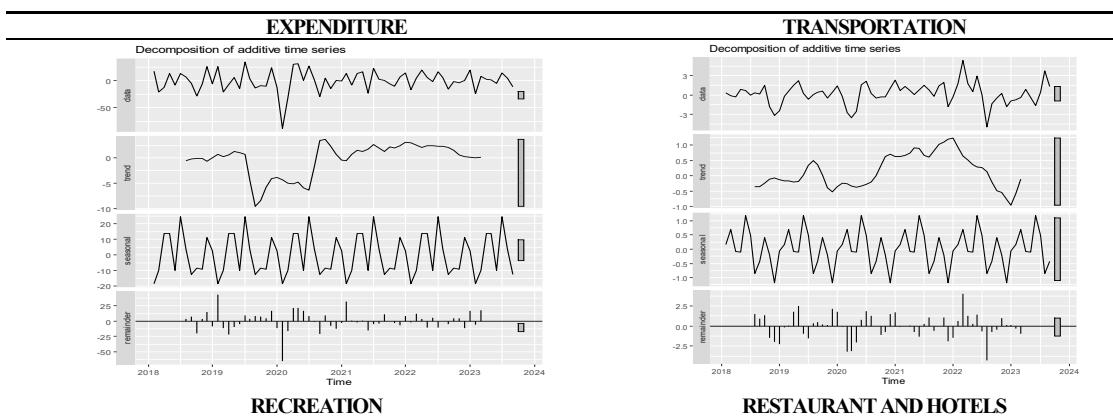
where (E_t) and (F_t) represents the actual values and forecast values at t the time respectively, n is the estimate values.

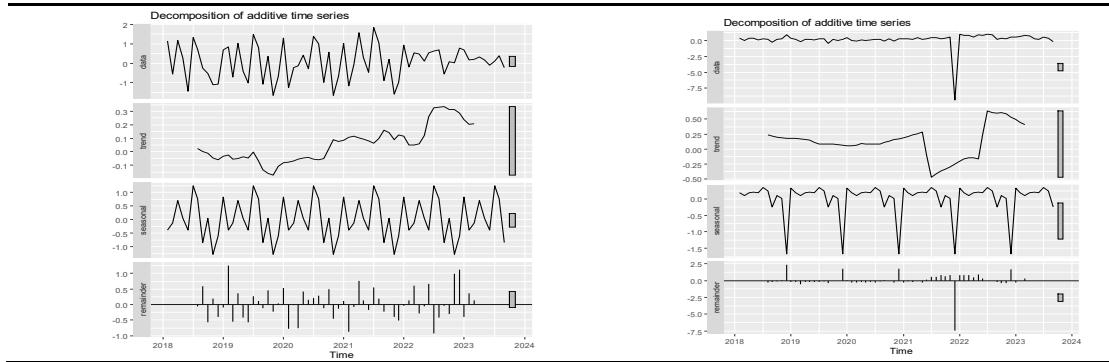
4. Results

4.1. Visualization and decomposition of the time series data

A time series exhibiting seasonality comprises three key components: a trend component, a seasonal component, and a remainder component (Wanjuki et al., 2021). To comprehensively analyze a time series, it is crucial to deconstruct it into its three fundamental constituents. Seasonal decomposition was utilized to explore whether the series exhibits these essential components (Wanjuki et al., 2022). Table 2 also shows the time plots of the decomposition of each variables time series alongside the associated 3 components (seasonal, trend, remainder).

Table 2. Time plots.





4.2. Identification

From visual inspection and prior knowledge of the nature of each time series in the research the author identified the data to be seasonal and non-stationary. There were generally monthly seasonal patterns in the data. Therefore, SARIMAX was identified as a suitable modelling technique that automatically handles seasonal and non-stationary data (Alharbi & Csala, 2022). In the Augmented Dickey-Fuller (ADF) test, the null hypothesis is that the data has a unit root, implying it is non-stationary (Zhang et al., 2023). A Prob value of 0.000 indicates that the test statistic is very significant, and the result would reject the null hypothesis. Therefore, a Prob value of 0.000 typically suggests that the data are stationary, meaning it does not have a unit root.

Table 3. Augmented Dickey-Fuller (ADF) test of Expenditure.

Expenditure	t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic	-7.594034	0.0000
Test critical values:		
1% level	-3.538362	
5% level	-2.908420	
10% level	-2.591799	

Table 4. Augmented Dickey-Fuller (ADF) test of Transportation.

Expenditure	t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic	-9.404323	0.0000
Test critical values:		
1% level	-3.534868	
5% level	-2.906923	
10% level	-2.591006	

Table 5. Augmented Dickey-Fuller (ADF) test of Recreation.

Expenditure	t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic	-7.773190	0.0000
Test critical values:		
1% level	-3.552666	
5% level	-2.914517	
10% level	-2.595033	

Table 6. Augmented Dickey-Fuller (ADF) test of Restaurants and hotels.

Expenditure	t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic	-9.836399	0.0000
Test critical values:		
1% level	-3.534868	
5% level	-2.906923	
10% level	-2.591006	

4.2. Estimation and Diagnostics

This step has two parts, namely estimation and diagnostics. First, the values of the model's coefficients are estimated, and second, the residual values of the model are checked against the assumptions of SARIMAX modelling. A grid search was carried out using AIC and BIC as the model selection criterion to find the best model. Grid search is terminology in machine learning that refers to an automated process of training and evaluating a model. In the case of SARIMAX, models were automatically created with different combinations of seasonal (P, D, Q) and non-seasonal (p, d, q) terms selected from a range of values, e.g. zero and one, and their respective AIC values and BIC values were automatically calculated.

To find the best SARIMAX (p, d, q) (P, D, Q)s model, a grid search was conducted on 60 different combinations of seasonal (P, D, Q) and nonseasonal (p, d, q) parameters.

These parameters took either the value of zero or one. The seasonal parameter(s) was set as 12 to be able to extract Monthly patterns. This research performed a parameter search as well to determine the autoregressive order of p and the moving average order of q with the trend (d = 1) and seasonality (s = 12). The output from the parameter search indicates that the $[\text{SARIMAX}(2,1,1)(1,1,1)]_{12}$ model has the smallest AIC value and BIC value (AIC=594.98, BIC=599.42) respectively.

The efficacy of the $[\text{SARIMAX}(2,1,1)(1,1,1)]_{12}$ model can further be assessed by analyzing the residuals. The results of the diagnostic tests on

$[\text{SARIMAX}(2,1,1)(1,1,1)]_{12}$ are shown in Figure 2. Figure 2 shows the p-values for the Ljung-Box statistic. Given the high p-values associated with the statistics, this research cannot reject the null hypothesis of independence in this residual series. Q-Q plot show that the residuals roughly follow a normal distribution, most of the points passes through the straight line with few of the points very closed to the straight line. The results of the diagnostic tests satisfy the assumptions of SARIMAX modelling.

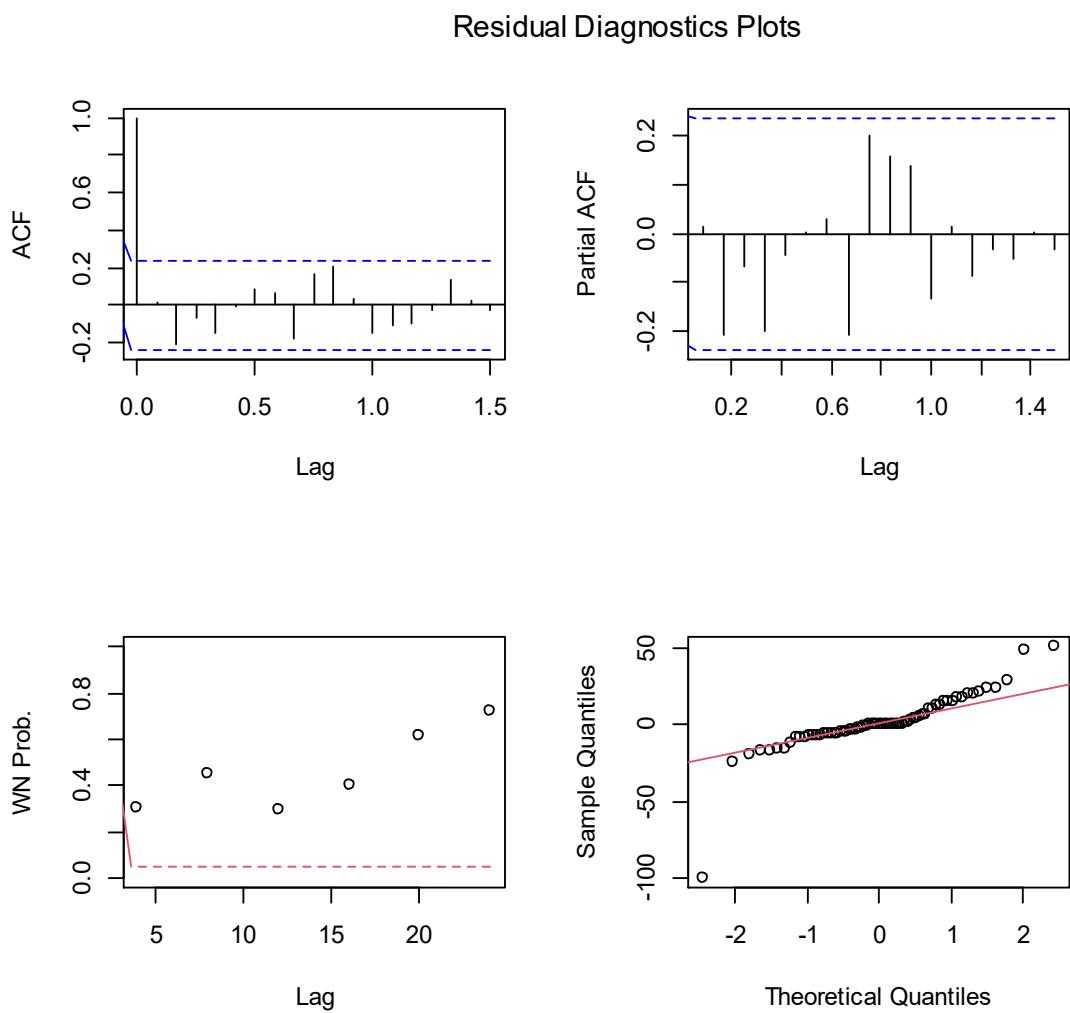


Figure 2. Diagnostic tests on the residuals of the model.

Figure 3 shows forecasted values with the actual values. The black line shows actual values, and the blue line shows forecasted values. The root mean square error (RMSE)

and mean absolute percentage error (MAPE) were used to examine the goodness of fit of the models and shows the value of prediction, RMSE and MAPE values are 5.02029 and 7.89903, respectively.

Forecasts from Regression with ARIMA(1,1,1)(1,1,0)[12] errors

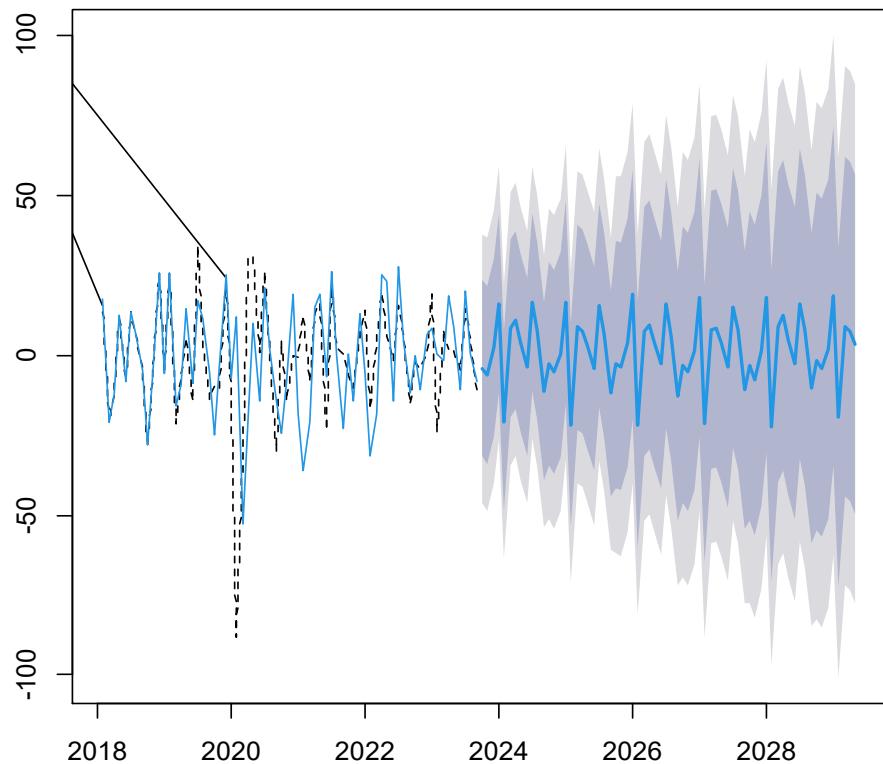


Figure 3. Forecasted and actual values.

5. Conclusion

5.1. Discussion

This study proposes a forecasting framework that incorporates exogenous variables, specifically the Consumer Price Index (CPI), into the prediction of domestic tourism expenditure. By integrating CPI data for various sectors such as Transportation, Recreation and Culture, and Restaurants and Hotels, the research advances the understanding of how macroeconomic indicators influence tourism spending patterns.

The model's performance evaluation further validates its effectiveness. The Root Mean Square Error (RMSE) and Mean Absolute Percentage Error (MAPE) values were 5.02029 and 7.89903, respectively, indicating a strong goodness of fit and robust predictive capability. These results confirm that the SARIMAX model can accurately capture short-term fluctuations in tourism expenditure driven by changes in consumer prices and cost-of-living conditions.

Overall, the forecasting results reinforce the study's main argument: that integrating CPI-based inflation dynamics into time-series forecasting provides meaningful insights for both academic research and industry applications. This evidence-based approach enhances the reliability of the model's predictions and supports informed decision-making for tourism policymakers and business stakeholders in South Korea.

5.2. Theoretical contribution

The utilization of a seasonal autoregressive integrated moving average model with exogenous variables (SARIMAX) in forecasting domestic tourism expenditure signifies a methodological advancement. By incorporating both the seasonal and trend components of the time series data along with external economic indicators like CPI, the study demonstrates an improved predictive accuracy compared to traditional time-series models. This underscores the significance of adopting sophisticated modeling techniques in tourism expenditure forecasting, potentially setting a benchmark for future research in the field.

The research emphasizes the role of tourism expenditure as a key driver of economic stability and growth. By analyzing the relationship between CPI and domestic tourism expenditure, the study offers insights into how inflationary pressures and changes in consumer purchasing power influence tourism spending behavior. This contributes to a deeper understanding of the economic dynamics underlying tourism consumption patterns, thus enriching theoretical frameworks in tourism economics and macroeconomics.

5.3. Practical contribution

The findings of this study hold significant implications for policymakers involved in tourism development and economic planning. By understanding the relationship between CPI and domestic tourism expenditure, policymakers can make informed decisions regarding fiscal and monetary policies aimed at fostering a conducive environment for tourism growth. Additionally, the forecasting framework proposed in this research can serve as a valuable tool for budget allocation and resource planning within government agencies responsible for tourism management.

For stakeholders in the tourism industry—such as tour operators, hospitality businesses, and destination management organizations—the insights derived from this study offer practical guidance for strategic decision-making under inflationary environments.

The findings reveal that fluctuations in the Consumer Price Index (CPI), particularly in Transportation, Recreation and Culture, and Restaurants and Hotels, have a significant influence on domestic tourism expenditure patterns in South Korea. For instance, rising transportation costs can suppress short-term travel frequency, while increases in restaurant and accommodation prices may shift consumer preferences toward shorter trips or lower-cost destinations. Conversely, moderate increases in recreation-related CPI can signal higher disposable income and stronger demand for leisure activities.

By integrating CPI dynamics into forecasting models, tourism enterprises can more accurately anticipate consumer spending shifts and design adaptive strategies. This includes dynamic pricing, flexible product bundling, and cost-efficient marketing approaches tailored to periods of inflation or deflation. The forecasting model proposed in this study thus enables tourism firms to not only predict expenditure trends but also to optimize operational and financial decisions based on expected economic fluctuations.

From a policy perspective, the incorporation of CPI into tourism expenditure forecasting enhances the government's ability to monitor economic vulnerability in the tourism sector. Policymakers can utilize these insights to design targeted subsidies, tax incentives, or inflation-indexed tourism support measures aimed at stabilizing demand during periods of economic stress. Furthermore, the framework can serve as a foundation for scenario-

based policy planning, allowing authorities to assess how future inflationary pressures could affect domestic tourism consumption and regional economic growth.

Overall, the strengthened discussion underscores the strategic and policy relevance of integrating CPI indicators into tourism expenditure forecasting, bridging the gap between macroeconomic analysis and tourism management practice in the South Korean context.

5.4. Limitations and further research

The present study offers a comprehensive analysis that yields valuable theoretical insights and practical implications. However, it primarily concentrates on monthly data, limiting the granularity of the analysis and potentially constraining the precision of forecasting outcomes. Moving forward, future research endeavors will leverage daily data, thereby affording a more nuanced examination and enhancing the accuracy of forecasting predictions. This strategic shift towards daily data integration holds promise for advancing our understanding of the dynamics under scrutiny and refining the predictive capabilities of the model, thus contributing significantly to the extant literature on the subject matter.

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