MODELING EXCHANGE RATE FLUCTUATION ON TOURISM DEMAND

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DECLARATION

This research project is my original work and has not been presented elsewhere for a degree or any other award.

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DEDICATION

This research project is dedicated to all the people who guided me in one way or another: my mother, Rose Bett. My father, William Bett, Daisy Bett, Valentine Jebitok, and all my brothers for their guidance and encouragement through this journey. My friends Shikanda, Jackline, Peter, Moris, Abel, Eunice, and many others, thank you for your continued support and encouragement throughout this journey. May the Almighty God bless you so much.

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ABSTRACT

This research examined the effect of exchange rate fluctuations on tourism demand in Kenya using Vector Autoregressive (VAR) and Bayesian Structural Time Series (BSTS) models. Secondary data from 2010 to 2023 was sourced from the Ministry of Tourism, Wildlife & Heritage, and the Central Bank of Kenya. The VAR model revealed significant causal effects from exchange rate fluctuations, particularly the US Dollar and Euro, on regional tourism proxied by the Ugandan Shilling, with no reverse causality detected. Exogenous exchange rate shocks accounted for a substantial portion of forecast uncertainties in tourism demand. The BSTS model effectively captured trend, seasonality, and inherent uncertainty in tourism demand forecasting, with residual diagnostics confirming model validity. Forecasts demonstrated a downward trend in tourism demand over time. Comparative analysis showed the BSTS approach outperformed the VAR model, with a significantly lower Root Mean Squared Error (RMSE) of 0.0635 compared to 0.9875 for VAR and a higher forecasting efficiency ratio of 15.55. The findings indicate that major currency exchange rate fluctuations significantly affect Kenya's tourism flow. Recommendations include adopting policies for controlling exchange rate risk, incorporating the BSTS model into forecasting frameworks, monitoring economic shifts and consumer preferences, and considering external factors in modeling. By adopting these recommendations and stochastic modeling approaches, policymakers and industry players can make informed decisions on exchange rate risks, pricing strategies, and marketing to boost regional tourism.

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ABBREVIATION AND ACRONYMNS

ARDL:	Autoregressive Distributed Lag
BSTS:	Bayesian Structural Time Series
CBK:	Central Bank of Kenya
FER:	Forecasting Efficiency Ratio
GARCH:	Generalized Autoregressive Conditional Heteroskedasticity
GDP:	Growth Domestic Product
MAPE:	Mean Absolute Percentage Error
RMSE:	Root Mean Scaled Error
VAR:	Vector Autoregressive

CHAPTER ONE

INTRODUCTION

1.1 Background Information

International tourism is another important sector for economic growth, foreign exchange earnings, and employment in Kenya, as it is important in poverty alleviation and infrastructure development (Agayi & Gunduz, 2020; Gechore et al., 2022). It is a fact that the country has several tourist attractions, from wildlife to cultural and natural beauty, which attract a large number of international tourists. However, the tourism industry has several challenges characterized by the factors that attract tourists to Kenya, spending trends, and expenditure (Tyitende, 2021). Thus, it is essential to forecast the demand for services in this sector to achieve sustainable tourism growth.

However, the tourism industry is subjected to numerous challenges that arise from events that shape the number of visitors and the amount of money they spend. Exchange rates are one such important factor. Exchange rate changes can affect a destination's cost-effectiveness and appeal to international visitors (Gil-Alana et al., 2019; Sharma & Pal, 2020; Athari et al., 2021). The appreciation of the local currency may make trips to Kenya expensive for foreign visitors, hence reducing the demand for the tourism product (Mwangi, 2022). Meanwhile, a weakened local currency will make Kenya attractive and affordable to tourists and may, therefore, enhance the demand for tourism (Njoya et al., 2022; Eric et al., 2022).

It is, therefore, essential to understanding the correlation between the tourism demand exchange rate volatility for policy and decision-making purposes in the tourism sector (Kisswani & Harraf, 2021; Jaipuria et al., 2021; Canbay et al., 2023). They can make the right choices, oversee the forex income, determine suitable pricing strategies, and create beautiful marketing methods that appeal to foreign visitors. As identified by earlier studies right up to the present study, exchange rates and tourism demand have a relationship in the countries of the world. For example, using the variables that determine internal tourism demand in Turkey and with the help of the analytical tool known as the gravity model, Ulucak et al. (2020). Thus, it could be concluded that the results show that Turkey’s origin country's per capita income, related exchange rates, and globalization influence the demand for tourism.

To analyse the causality between exchange rate volatility and tourism demand, Sharma & Pal (2020) employed the aid of Non-linear Autoregressive Distributed Lag (NARDL) model with specific focus on India. The authors of this particular study postured that exchange rate volatility and tourism demand in India was an asymmetric correlation. At times, the traditional techniques used are ineffective in determining the dynamics of the tourism demand (Naimoli, 2020). VAR and BSTS models are more favorable in giving more advanced precision to forecasts or some factors (Yu, 2022).

Causal VAR models enable one to present multi-directional causality; for the present study, it is pertinent to look at Causal VAR of tourism demand and exchange rates (Tgoda, 2023). As with the above discussion on the VAR models, they help determine the short-run and long-run impacts of exchange rate volatility on tourism demand owing to the effects of the lagged variables (Kisswani et al., 2022).

Therefore, the models extracted from BSTS are easily adaptable to help model and forecast tourism demand in Kenya. These models also help to model the time series, cycles associated with the seasonality of the tourism activity level, and inherent randomness. BSTS models are particularly appropriate for integrating prior knowledge and updating forecasts at a subsequent time when additional data becomes available; for this reason, they are of probabilistic form. Hence, a more accurate and diverse form of forecasting appears to capture the details of the demand for Kenya’s tourism (Berbekova et al., 2021).

Therefore, to achieve the objectives of this research, this study seeks to establish the volatility of tourism demand and exchange rates in Kenya using the VAR model. The research, therefore, constructed a BSTS model to forecast the tourism demand in Kenya relative to the foreign exchange rates. A performance comparison of the test VAR model with the benchmarked BSTS model to determine which models are suitable for modeling the demand for tourism in Kenya has also been established based on parameters such as accuracy, robustness, and efficiency.

1.2 Problem Statement

The positive impacts of tourism on Kenya's economy include employment creation, foreign exchange earnings, and economic growth (Njoya & Seetaram, 2018; Gechore et al., 2022; Mathew et al., 2021). Tourism is one of the most dynamic and globally connected industries, so forecasting demand for it is crucial to efficient management and growth. Exchange rates have also been observed to influence the tourism demand in Kenya because they define the cost and, therefore, the destination's appeal (Kimani, 2021).

Past researches reveal the established association between tourism demand and exchange rates in different countries, and this explains the effect of exchange rate volatility on tourism demand (Adeola & Evans, 2020; Rosselló-Nadal & He, 2020; Kimani, 2021; Wamboye, 2020). However, a significant statistical gap exists in the Kenyan context regarding the nature and intensity of this relationship. Traditional forecasting models often fail to capture the complex dynamics between exchange rates and tourism demand, particularly in emerging markets like Kenya. Most studies on Kenyan tourism demand have relied on conventional time series models, which may not adequately account for the intricate relationships between multiple variables and time-varying effects. Furthermore, insufficient research comparing the performance of different advanced forecasting models in the context of Kenyan tourism demand leaves uncertainty about the most effective approaches.

Therefore, policymakers and industry players must understand this relationship well to manage the exchange rate risk, set the pricing of the products and services, and have a policy for marketing the destination to international tourists. To address these gaps, this study employs VAR and BSTS models to investigate the impact of exchange rate fluctuations on tourism demand in Kenya. These stochastic modeling techniques can enhance forecasting accuracy and incorporate relevant factors in the models (Meisenbacher et al., 2022; Yu, 2022; Kisswani et al., 2022). By comparing these advanced approaches, the research aims to provide a more comprehensive and accurate understanding of the relationship between exchange rates and tourism demand, enhancing the forecasting capabilities available to policymakers and industry stakeholders in the Kenyan tourism sector.

1.3 Justification of the Study

The study helped overcome the traditional models' deficiencies in describing the demand for tourism. Traditional models do not consider the relationships between several factors and do not consider the relationships of change and time. This study is significant because it explains the relationship between the demand for tourism and exchange rate fluctuations in Kenya and how this can be improved to increase forecasting accuracy for the benefit of policymakers and industry players. The study helped make informed decisions and form appropriate sustainable tourism development tactics. Therefore, this study applied stochastic models such as VAR and BSTS to better understand the demand for tourism in Kenya, enhance the accuracy of forecasts, and empower decision-makers.

This research study seeks to address whether the VAR or BSTS models are the best for forecasting tourism demand in Kenya by comparing the results of the two models. The comparison involved factors such as accuracy, robustness, and computational process and thus helped in understanding the weaknesses of each model. This evaluation helped improve the forecasting methods in the sphere of tourism. Thus, it is more or less self-evident that there is a need to fill the existing gaps in the literature about the connection between tourism demand and exchange rate fluctuations and supply enough information for stakeholders.

1.4 Research Objectives

1.4.1 General Objective

To analyze the effect of exchange rate fluctuation on tourism demand.

1.4.2 Specific Objectives

i) To Predict the impact of the exchange rate on tourism demand in Kenya using Vector Autoregressive (VAR) model.

ii) To forecast the tourism demand based on the Kenya exchange rate using the Bayesian Structural Time Series (BSTS) model.

iii) To evaluate the efficiency of BSTS and VAR Models.

1.5 Hypothesis

i) There is no significant impact of the exchange rate on tourism demand using VAR

ii) There is no significant impact of the exchange rate on tourism demand using BSTS

iii) There is no significant difference in predating tourism demand on exchange rate using BSTS and VAR model

1.6 Scope of the Study

This research investigates the effect of exchange rate changes on tourism demand in Kenya and its modeling. It is a forecasting tool that predicts the demand for tourism using Stochastic Models: Vector Autoregressive (VAR) and Bayesian Structural Time Series (BSTS). The research used secondary data obtained from reputable sources like the Ministry of Tourism and Wildlife and the Central Bank of Kenya. The scope includes comparing the forecasting performance of VAR and BSTS models for accuracy, robustness, and computational efficiency. The research, however, is confined to Kenya and the interaction between demand for tourism and exchange rates.

1.7 Assumptions of the Study

Since the tourism demand and exchange rates are assumed to be both linear and stationary, the application of the VAR models and the BSTS models is possible. The variables adopted in the models are exchange rates and tourism demand; these are issues believed to be responsible for changes in demand for tourism.

Other factors influencing tourism demand, such as income levels, political stability, security, and marketing efforts, are considered constant or appropriately specified in the chosen models. This research focuses on exchange rate volatility and its effect on tourism demand. The distribution of the data used for modeling and forecasting is normal. This assumption is required because VAR and BSTS models often assume normal errors. The historical trends and correlations between the exchange rates and tourism demand will persist, and future tourism demand will be forecasted using historical information. The VAR and BSTS parameters are assumed constant over the forecast horizon, implying that the relationships between the variables and the data patterns remain the same.

CHAPTER TWO

LITERATURE REVIEW

2.1 Effect of exchange rate fluctuation on tourism demand

Much empirical literature remains on the topic of previous and current relations between exchange rate volatility and tourism in given countries and broader regions. Some studies have considered this relation in the context of individual countries. Sharma & Pal et al., 2020 conducted an empirical study regarding the relationship between exchange rate fluctuation and tourist traffic in the Indian region. The employed model was the nonlinear autoregressive model. Based on the results obtained, there is evidence that India's tourism demand is responsive and conditionally endogenous to the exchange rate risk. Hence, this paper also adds to the world's knowledge by understanding the role of exchange rate volatility on India's tourism demand.

As a research problem, Tung (2019) sought to determine the effect of exchange rate fluctuation on the number of foreign tourists in an emerging tourist nation: Vietnam. Thus, the study employed time series data and, through the cointegration regression analysis, found a long-run equilibrium relationship between the exchange rates and tourism demand, revealing a positive association. It also supported the hypotheses by finding that the exchange rate is another determinant of the emerging tourism markets aspiring to attract international tourists.

Tung & Thang (2022) conducted their research among a more extensive population of developing countries than the studies mentioned above. The authors of their study used a panel data analysis across the country and other countries, and they found that there was exchange rate asymmetry in the volatility of foreign tourist arrivals. For instance, it was recently established that currency depreciations positively impact the variable of interest: tourism demand. At the same time, currency appreciation has also been pointed out as negatively affecting the inbound tourism flow. This type of relationship is rather interesting and can be viewed as a clear reflection of the interdependence between exchange rates and tourism, especially considering the development dimension.

Consequently, some other works have been devoted to exploring this kind of relation taking place in particular states. In an empirical analysis aimed at establishing the connection between exchange rate volatility and Nigeria's tourism sector, Peace et al. (2016) used the vector error correction model. The study's findings exposed that the formulated relationship was negative because the variation in exchange rate affected the efficiency and effectiveness of the tourism sector in Nigeria. In the same line today, Rafiei & Abbaspoor (2022) analyzed the influence of exchange rate volatility on domestic tourism consumption in Iran. The study used a modified social accounting matrix coupled with a CGE model to assess the impacts of a 50% upward change in the exchange rate. The results revealed the total decrease in domestic tourism demand across all households with the enhancement of export activities in several sectors. The hotel sector, a proxy for inbound tourism, shows increased demand. The study highlights the non-homogeneous consequences of exchange rate fluctuations across sectors and emphasizes the need for comprehensive analysis when formulating exchange rate policies.

Other studies have concentrated on developed tourism markets. Revisiting the Italian context, Quadri & Zheng (2011) confirmed a positive relationship between a weaker domestic currency and increased inbound tourism demand. Their findings agree that currency depreciation can enhance a destination's attractiveness and affordability for international tourists, boosting tourism inflows. Accordingly, Irandoust (2019) has added to the earlier literature on exchange rate changes and tourism demand to the non-synchronous association between exchange rate changes and tourism demand in ten European countries. To advance the prior literature, this work does not assume that the coefficients of appreciations and depreciations on tourists' demand are symmetric. The method applied in this research is the hidden cointegration analysis within a likelihood-based panel data procedure to analyze the long-run association between tourism demands and fluctuation in exchange rate. The study showed that tourism is not an evenly sensitive product concerning exchange rate changes, which depend on directional and magnitude changes. The study is centered on the work's financial implications of the findings; the method used in this research could be useful in forecasting the exchange rates for the currencies.

Another study by Tang et al. (2016) was on the effect of exchange rates on tourism demand by examining the co-integration of the two variables with emphasis on China's inbound tourism from selected countries. To this end, the study used copula-GARCH models to offer a new view of the connection. The results based on the statistical data analysis indicated that the exchange rate volatility does not significantly affect the variability of China’s inbound tourism from the countries of interest. All the countries, except Russia, appear to have low sensitivity to fluctuations in the exchange rate and, therefore, may be considered to have low-risk management when it comes to a highly volatile exchange rate system. The study also revealed a need to examine the impact of exchange rates on tourism demand. It concentrated on the applicability of the results to destination managers and travel agents in assessing the exchange rates in equations of international tourism demand.

Asymmetries and price rigidities were examined by Karimi et al. (2019) concerning inbound tourism in Malaysia. Their study discovered that Malaysian tourism was comparatively more sensitive to depreciation than exchange rate appreciation given the prevalence of price rigidities that influence demand. In light of the theoretical framework, Loganatan et al. (2019) contributed to previous research that investigated the exchange rates and tourism demand by investigating the impact of exchange rates, price competitiveness indices, and domestic taxation on the international tourism demand in Malaysia. The quantitative approach uses quantile regression, and the data is collected monthly from 1996 to 2017. This paper’s empirical analysis revealed that Malaysia’s sales tax has a significant adverse effect on the international inbound tourism demand, especially at the middle levels of the distribution.

In addition, it was found that Thailand’s price competition enhances the Malaysia's tourism demand. On the other hand, although Indonesia exchange rate competitiveness is good, this fuels demand for tourism. The results of this work may be useful for Malaysian authorities who make suggestions concerning the improvement of launched fiscal policies and the constant increase of foreign tourist demand in the following years. Consequently, examining the previous literature, Santana-Gallego et al. (2010) examined the effect of the exchange rate on tourism demand with the stress on exchange rate regimes of international tourism. In this paper, panel data analysis has been employed, and further analysis of the common currency and its effect on tourism has been discussed. The conclusion, therefore, was that there is an inverse relationship between the ‘common currency’ on one hand, and tourist arrivals on the other. Inflation figures were also calculated to examine the condition of exchange rates, and referring to the statistics, it was found that rather stiff rates of fluctuation are good for tourism. The results of the given analysis and conclusions contribute to the explanation of the disparities of the literature about the effects of exchange rate volatility and stress the significance of exchange rate regimes influencing tourist traffic.

That is why the variety of the methods chosen by the researchers allows to reveal different dynamics: Dhaoui et al. (2017) investigate the exchange rates, oil prices and tourism demand in Tunisia with the help of the ARDL bounds testing technique. Their research shows that the real effective exchange rate and tourist arrivals are linked oppositely 'causally.' Meo et al. (2018), in this research, focused on the role of exchange rates for tourism demand and investigated the effect of asymmetric behavior on oil prices, exchange rates, and inflation on the tourism demand of Pakistan. The best-fitting model for the analysis was the nonlinear autoregressive distributed lag (NARDL) model, and the cointegration test done was the limit test. The results show a long-run co-integrating but unbalanced relationship between oil prices, exchange rates, inflation, and tourism demand. These lead to an improved understanding of the complex nexus between Pakistan's exchange rate and tourism demand.

Several studies have explored the impacts of exchange rate volatility on tourist flows originating from different source markets. Agiomirgianakis et al. (2014, 2015a, 2015b) conducted investigations that found evidence suggesting exchange rate uncertainty can deter tourist inflows into destinations like Turkey, Iceland, the UK, and Sweden. Ongan et al. (2017) have done a piece of work under the heading of 'Actual exchange rates and income implications on inbound tourism demands: A case study of select European Union countries to the USA.' The study used panel cointegration, where the estimation method employed was the cross-sectional dependence test and the common correlated effects model. The empirical results showed that tourists visiting the USA are relatively more sensitive to the change in real exchange rate vis-a-vis GDP. This research also revealed that the UK was highly sensitive to the real exchange rate given that it is out and has plans to leave the Eurozone of the European Union. Employing eating-out prices from the HICP and utilizing the real exchange rate increases the methodological innovation of the study.

Acar (2012) analyzed the co-integration between Turkey's tourism demand and exchange rate employing the dynamics conditional correlation GARCH, commonly called the DCC-GARCH model by Engle. The work analyzes the demand for tourism from the Eurozone, the USA, and the UK to Turkey. The analysis results showed that for the Eurozone and the USA, the correlation between Client Demand for Tourism and Exchange rate is positive, which implies that destinations receive higher tourism inflows if the home currency of the visitors is stronger. However, a clear positive relationship has not been identified for tourism demand in the UK. It appreciates the centrality of the exchange rate factor in the exanimation of and prognosis of tourism demand momentum (Matthew et al., 2021).

2.2 Forecasting tourism demand based on exchange rate fluctuation

Numerous studies have been conducted to forecast tourism demand using exchange rates. For instance, Alamsyah & Friscintia (2019) used the accurate tourism demand forecasting model for Indonesia. They stressed the further development of the tourism industry and its important role as one of the leading sectors that affect foreign exchange earnings and employment in the national economy. Potential demand and supply are critical factors that must be balanced to enhance tourism. The independent variables adopted by the researchers include gross domestic product (GDP), consumer price index (CPI), and exchange rates of five principal visitor countries to Indonesia to forecast the number of tourists. The study also focused on the issues related to the nonlinear nature and high variability of the data characteristic of tourism as a seasonal and rather sensitive industry. The study concluded that the best architecture of the forecasting model for the monthly tourist arrivals in Indonesia was one hidden layer node and 31 hidden neurons. Studies of this nature establish that artificial neural networks could be relied on to give accurate estimates of the demand and resources for tourism.

Xie et al. (2021) used big data to forecast the demand for Chinese cruise tourism. Such a situation can be explained by the fact that the growth rate of cruise travelers in China has declined gradually. The level of financial risks associated with investments in the cruise tourism industry has risen, which points to the necessity of predicting the demand for cruise tourism in China more accurately to make the right investment decisions and draw up appropriate plans. The authors applied a least squares support vector regression model with a gravitational search algorithm (LSSVR-GSA), which includes Baidu search query data and economic indices as predictors. Applying the Gravitational Search Algorithm for the hyperparameters of the LSSVR model enhanced the forecast's accuracy. Therefore, the results of LSSVR-GSA, in which the original mobile keywords and economic indices are partially selected, are the most accurate. The study also shows that the research methodology is sufficient, and big data can be used to predict China's cruise tourism demand.

Usman et al. (2021) analyzed the impact of currency fluctuation, energy prices, and tourism on restaurant and hotel prices. This paper used the multiple structural break cointegration test and the flexible ARDL techniques for the analysis. The analysis established that the exchange rate had an inverse relationship with restaurants and hotels, where a rise in the exchange rate resulted in a price decline.

Wamboye et al. (2020) studied and realized the factors that affect global tourism demand in Tanzania, which is a key area for Africa's economic development, foreign exchange, and employment. The study used Tanzania's top fifteen tourist supply countries from the year 2000 to the year 2016 panel data. Several panel data estimation methods were employed to analyze the factors affecting international tourism demand. The findings showed that tourist income and Tanzania's infrastructural development were the leading drivers of the global tourism demand. Based on the findings of this study, it is recommended that policymakers and stakeholders should invest in infrastructure, come up with appropriate tourism packages for high-income countries, and embark on appropriate marketing strategies to position Tanzania as a competitive tourism destination.

2.3 Evaluating the efficiency of VAR and BSTS models

Previously, VAR and BSTS models were used for forecasting, especially in financial forecasting. Not many researchers have tried to evaluate the efficiency of the two models by comparing the accuracy measures. For instance, Ray et al. (2021) employed a study to establish the extent to which news sentiment impacts the stock market. They compared the effectiveness of two modeling techniques: two specific types of models, namely VAR and BSTS models. The authors recognized that even though the VAR and BSTS models are used frequently in financial prediction, the BSTS model offers a clearer picture and control of uncertainty. However, the BSTS model assumes linearity, while the real structure of texts is often nonlinear to some extent.

Kohns (2023) worked on interpretable forecasting and risk estimation using high-dimensional Bayesian methods. He noted that BSTS models are good for large dimensional data and provide easily interpretable results, which are important in nowcasting. Duan (2015) devoted his doctoral thesis to the application of nowcasting with the help of the BSTS-U-MIDAS model.

According to Kohns & Bhattacharjee (2023), the variable was forecasted by applying Google Trends and the Bayesian structural time series model. Their work also described how other external data sources, such as web search data, can be incorporated into BSTS models for better nowcasting. This paper has also utilized the BSTS model to establish the relationship between the change in industrial structure and fiscal revenue in Shenzhen, China, as Shu & Qi (2023) recommended. They also disclosed information on the general usage of BSTS models to perform structural alterations in time series and the appropriateness of the models in managing structures of time series data.

Zhang (2024) used ARIMA and BSTS for comparison purposes to forecast the electricity prices of the major cities on the west coast. It was observed from the study that BSTS models were more capable of representing the seasonal trends of the electricity price data than the ARIMA models. Schmitt et al. (2018) later discussed how these programs affect many households using Bayesian structural time-series estimates of causal impact.

Scott & Varian (2015) applied the Bayesian variable selection in nowcasting economic time series. Their approach involved the use of BSTS models together with variable selection techniques that assisted in the identification of the most appropriate predictors as well as the improvement of nowcast efficiency. Ludwig et al. (2016) compared the effectiveness of the Bayesian structural time series models using the case of electricity prices. Their conclusion established that BSTS models are effective and less time-consuming in handling large time series data.

Thus, the literature analysis showed that BSTS models are applied for nowcasting, risk assessment, and policy evaluation in particular sectors. There are some benefits of the BSTS models, which are as follows: they can capture high-dimensional data, incorporate auxiliary information, accommodate nonlinearity, and are easy to interpret. However, it is admitted that there are some limitations to the current approaches, which include the linearity assumption and variable selection issues, and researchers call for their extensions. The literature generally highlights that BSTS models are useful in time series analysis and forecasting, especially if the right model augmentation and variable choice methods are employed.

2.4 Summary of the Literature

The previous research on the impact of exchange rates on tourism demand has generated many studies with different results depending on the country, methodological approach, and other factors. Another commonality is that the volatility of the exchange rate has an interaction effect with tourism demand, whereas Sharma & Pal (2020) and Tung & Thang (2022) in their research on developing countries. These works highlight the complex relationship between the exchange rate and demand for tourism; while depreciation in the exchange rate increases demand for tourism, appreciation decreases the demand (Zachariah et al., 2023).

Some research works have gone deeper into country-level investigation and revealed somewhat different patterns. Peace et al. (2016) established a negative correlation between exchange rate volatility and the tourism industry in Nigeria, while Rafiei & Abbaspoor (2022) showed that the impact is sector-specific and heterogeneous in Iran; the hotel industry receives a higher number of tourists when the currency is devalued. These results imply the need for further research and development of specific exchange rate policies for the countries that rely on the tourism industry.

Scholars have also examined the effects of exchange rate mechanisms and currency communities on tourism traffic. Santana-Gallego et al. (2010) noted that the degree of flexibility of the exchange rates and the adoption of a single currency are major factors that affect tourist arrivals. Irandoust (2019) refuted the symmetry hypothesis, meaning that the European tourism demand responds differently to the changes in the exchange rate – appreciation and depreciation (Lawal et al., 2022).

Technological advancements that have occurred in the field of economics have given new insights into the relationship between the exchange rate and tourism demand. Tang et al. (2016) used copula-GARCH models to investigate China's inbound tourism, and it was observed that exchange rate volatility has a rather limited impact on arrivals. However, a risk aversion was observed among the Russian visitors during periods of extreme depreciation of the Ruble. Ongan et al. (2017) used a panel cointegration approach to establish that EU tourist demand for the USA is more responsive to real exchange rate shock than GDP shock.

Scholars have also paid attention to issues related to asymmetry and price stickiness in influencing the tourism demand reactions to exchange rate fluctuations. Karimi et al. (2019) highlighted that Malaysian inbound tourism responded more to depreciations than appreciations because of price rigidities. Loganatan et al. (2019) adopted quantile estimation methods, highlighting the significant influence of price competitiveness indices and domestic taxation on Malaysia's international tourism demand across quantiles.

Numerous studies have been conducted on forecasting tourism demand based on exchange rates, employing diverse methodologies. To predict the Indonesian tourism demand, Alamsyah & Friscintia (2019) used the artificial neural network model; the input variables include GDP, consumer prices, and exchange rates from the major tourist-generating countries. Xie et al. (2021) developed a hybrid least squares support vector regression model integrated with gravitational search algorithm optimization applied to big data sources such as Baidu search queries and economic indices for predicting the Chinese cruise tourism demand.

Many studies have analyzed the effect of the currency exchange rate, energy cost, and tourism on restaurant and hotel prices utilizing Structural break cointegration and the Flexible ARDL model as a framework. According to Wamboye et al. (2020), Tanzania's global tourism demand determinants include tourist income and infrastructure development, estimated through panel data estimation techniques.

Even though assessing the efficiency of forecasting models has been a rather popular topic, few papers have been devoted to comparing the accuracy measures of VAR and BSTS models. Ray et al. (2021) have discussed these models in the context of stock market movements with news sentiment in which, although the BSTS model is more explicit and effective in dealing with uncertainties, it cannot capture the nonlinear structures because of its linear assumption.

BSTS models have been discussed in the literature recently for their capability to work with large numbers of features, involve covariates, model nonlinear effects, and offer easy-to-interpret results. Kohns (2023) and Duan (2015) looked at the BSTS models for interpretable nowcasting and risk estimation, and Kohns and

Bhattacharjee (2023) applied how they can incorporate search data for enhanced growth nowcasting accuracy.

Industry-specific applications have also applied BSTS models. Shu & Qi (2023) used the evolution of industrial structure and fiscal revenue for Shenzhen in China, Zhang (2024, used the BSTS and ARIMA models to compare the electricity price forecasting model. Schmitt et al. (2018) generalized BSTS models to estimate the causal effects of interventions in multiple time series and demonstrated the framework's applicability to policy evaluation. Scholars have agreed that more extensions and enhancements are required to fix the weaknesses of BSTS models, including the linearity assumption and variable selection. Scott and Varian (2015) presented the Bayesian variable selection approaches to BSTS models to select important predictors and improve nowcasting precision; Ludwig et al. (2016) discussed their applicability and speed for big data.

The literature on the exchange rate-tourism demand relationship is a colorful and diverse picture of findings, methods, and complexities. This research explores the factors that alter the asymmetric responses of exchange rates on tourism demand, price rigidity, market characteristics, and macroeconomic linkages. As for forecasting, various modeling strategies have been incorporated and applied using artificial intelligence, big data analysis, and econometric models. The assessment of the efficiency of the forecasting models, especially in comparison to VAR and BSTS, remains an area that has been studied to a very limited extent, which opens up opportunities for further research and methodological developments.

2.5 Research Gaps

There is a need for further research on the effect of exchange rates on tourism demand in emerging economies and developing nations, as most of the current literature has focused on developed nations. The influence of exchange rate volatility on travelers' destination preferences and travel patterns could be the subject of additional study.

Although the literature provides valuable insights into forecasting tourism demand based on exchange rates, future studies must address several research areas. First, there is a need for additional research on tourism demand forecasting models specific to various regions and countries, considering their distinctive characteristics and tourism-influencing factors. Furthermore, the literature could be enriched with papers that explore the application of high technologies, including machine learning and artificial intelligence, to enhance the accuracy of tourism demand forecasts.

There is still a lack of research on the effectiveness of VAR and BSTS models, making identifying relevant information scarce. Thus, more research is required to fill the existing gap in the literature. Further studies could address this deficiency by using more comparative studies to compare the performance of these models in other forecasting domains apart from the two above-discussed domains: tourism demand and exchange rate fluctuation. As Ray et al. (2021) noted, even though VAR and BSTS models are widely utilized in financial forecasting, the effectiveness of applying them in tourism demand forecasting based on the exchange rates has not been investigated comprehensively.

However, the authors have also discussed the stagnation in not only the development of the method but also the improvement of the methods of how to handle BSTS models' problems, such as the problem of linearity and variable selection difficulty that has been highlighted by Ray et al. (2021), Kohns (2023), Shu & Qi (2023), Peace et al., (2016), and Rafiei & Abbaspoor (2022). For future research, it might be possible to increase the efficacy and applicability of BSTS models by employing nonlinear forms or variable-selection techniques to include additional variables that might explain non-linear relationships between exchange rates and tourism demand.

It may be necessary to understand how far the two models can go when used in fields apart from financing and in which field the use of both models is applicable. For example, Kohns (2023) discussed applying high-dimensional Bayesian methods and BSTS models for interpretable nowcasting and risk assessment; Shu and Qi (2023) employed BSTS to study the effect of industrial structure transition on fiscal revenue. Such studies show the applicability of these models and point to future research directions in various areas.

Furthermore, there is limited literature on the interaction between exchange rates, price rigidities, markets, and other macro variables on tourism demands (Ray et al., 2021; Kohns, 2023; Shu & Qi, 2023; Peace et al., 2016; Rafiei & Abbaspoor 2022). Future research could incorporate these factors to better understand the numerous factors likely to affect tourism demand.

Little has been documented on the use of sophisticated techniques like deep learning and Bayesian search for tourism demand forecasting models using exchange rates (Ray et al., 2021; Kohns, 2023; Shu & Qi, 2023; Peace et al., 2016; Rafiei & Abbaspoor 2022). Given that these techniques are being increasingly applied in different fields, the possibility of increasing the accuracy of demand forecasting in tourism is quite apparent.

Similarly, Peace et al. (2016) and Rafiei & Abbaspoor (2022) have noted that future research will need to undertake country and regional-level analysis to capture better the heterogeneity in the exchange rate-tourism demand nexus across different economies and market conditions (Ray et al., 2021; Kohns, 2023; Shu & Qi, 2023; Peace et al., Such localized studies could help in the formulation of specific exchange rate management strategies and policies for the tourism-dependent economies.

Few researches have been done to compare the efficiency of VAR and BSTS models, thereby creating the research gap. Thus, it is necessary to carry out further investigation of the problem to fill the gap in the existing knowledge. Future research could help fill this gap by undertaking other comparative studies to compare the performance of these models in forecasting domains other than tourism demand and exchange rate fluctuation. Furthermore, it is necessary to consider the possibility of the BSTS model to analyze nonlinear structures and study how to enhance the flexibility and accuracy of this model. Extending the use of VAR and BSTS models to fields other than finance could also be useful in revealing the effectiveness of these models and in discovering other areas that could benefit from these models.

2.6 Conceptual framework

These conceptual frameworks guide how the research work will be developed and structured to show the relationship between exchange rate fluctuations and tourism demand in Kenya. These variables are essential to the theorization of PP, upon which the research framework is further anchored to some of the potential theoretical models.

2.6.1 Key Variables

Exchange Rate Fluctuations: Exchange rate fluctuations, which are the changes in the value of foreign currencies relative to the Kenyan shilling, are the first of the positional strategy's key independent variables in this study. The research will consider commonly used currencies of great importance to Kenya's tourism business, including US Dollars, British Pounds, Euro, Ugandan Shillings, and Tanzanian Shillings. These fluctuations are assumed to affect the costs of travelling and, hence, the volume of international tourist traffic to Kenyan destinations.

Tourism Demand: The dependent variable is tourism demand, which is captured by the total number of tourists visiting Kenya from other countries. This research proposes the following hypothesis, The exchange rates influence tourism demand in Kenya because changes in exchange rates make Kenya either relatively expensive or cheap to visit depending on the exchange rate of the foreign currency to the Kenyan shilling. Control Variables: In the same regard, other factors may affect tourism demand, such as macroeconomic factors, security issues, and seasonal factors. These are depicted in the study to control for the effect of exchange rate change on tourism demand.

The framework is grounded in several theoretical perspectives:

Price Elasticity of Demand: This new school of economic theory proposition holds that price sensitivity is characteristic of the demand for a good or service. Relative to the idea of tourism, exchange rate changes may influence the prices of traveling to Kenya due to price changes. Currency Valuation and International Competitiveness: When the shilling becomes stronger, it becomes costly to account for in Kenya's tourism industry, making it less attractive to foreigners; this is the other way round; when the shilling becomes weaker, it is cheaper and thus more attractive to foreigners to visit the country. It will also provide the framework for analyzing how exchange rate volatility affects tourism inflows.

Stochastic Modeling: Because exchange rate fluctuations are more or less stochastic or random, this study uses stochastic models to quantify the impact of exchange rate fluctuations on tourism demand. It shows that these models are useful for analyzing the time series data where both random and systematic movements are experienced.

2.6.2 Model Identification and Justification

The paper employs stochastic models such as the Bayesian Structural Time Series (BSTS) and other time series modelling to analyze the effect of exchange rates on tourism demand. These models are chosen based on their ability to:

Capture Trends and Seasonality: BTS decomposition can derivate the stochastic time series of the exchange rates and tourism demand; their trend and seasonality can also be hydrolyzed, which helps understand the relationship between exchange and demand. Incorporate Uncertainty: Stochastic models incorporate randomness and unpredictability, characterizing the exchange rates and making these models useful for predicting tourist traffic under varying conditions. Conduct Retrospective Analysis: The models enable past data to be gathered and examined from the point of view of the effects of tourism demand on past changes in exchange rates. Establishing a long-run relationship between these variables is crucial when performing long-run forecasts.

2.6.3 Hypothesized Relationships

Large movements in relative currency prices mean there will be a corresponding change in tourism demand; when the currency is strong against the Kenyan shilling, tourist arrivals are low, implying that tourist arrivals are high when the currency is weak. This product's impact will depend on the currency in question. A considerably more significant impact will be generated from the key tourist source countries such as America, the United Kingdom, and the Eurozone region. Such factors as fluctuations in the exchange rates that affect local tourists will be mitigated by factors such as seasonality and global economic conditions that affect tourism demand.

The exploratory part aims to identify new information regarding the exchange rate-tourism demand nexus. The analytic part analyzes all the findings with the help of sound stochastic models. This knocks the study’s relevance and ability to apply its findings to other situations because of the historical orientation the retrospective analysis gives to the framework. Guiding Hypothesis Development: This feeds into the genesis of the hypothesis about the effects of exchange rates on tourism demand. Supporting Model Selection: The identified framework offers a basis for choosing stochastic models and a reason for their application in the present investigation.

CHAPTER THREE

RESEARCH METHODOLOGY

3.1 Research Design

The research method for this study is exploratory and analytic, incorporating a retrospective approach. This design uses stochastic models to evaluate the effects of exchange rate volatility on Kenya’s tourism demand. The exploratory aspect of the design aided in obtaining a better understanding of the relationship between exchange rates and tourism demand in Kenya, as this relationship is relatively unexplored. Using exploratory research, the study seeks to uncover new insights and identify possible patterns or tendencies.

3.2 Data Source and Processing

The secondary data for this study was obtained from the Ministry of Tourism, wildlife & heritage, and the Central Bank of Kenya (CBK). The data covered 14 years period ranging from 2010 to 2023. The data for exchange rate is freely available at the CBK website *https://www.centralbank.go.ke/*, whereas the tourism demand data was requested by the Ministry of Tourism, Wildlife & Heritage by mailing them. The email contained the type of data, the period covered by the data, and the approved research proposal. According to CBK statistics, tourists visiting Kenya's most commonly used currencies include the Ugandan Shilling, Tanzanian Shilling, US Dollar, Euro, and British Pound.

The Ministry of Tourism, wildlife & heritage collects and maintains information on tourist arrivals, expenditures, and other relevant tourism indicators (Mayaka & Prasad, 2012). This data provides valuable insight into the demand for tourism in Kenya. In contrast, the Central Bank of Kenya provides exchange rate information, which is crucial for analyzing the impact of exchange rate fluctuations on tourism demand.

Cleaning of data is another important process in the research process in order to maintain the credibility of data used in the analysis. Tasks involve assessing for missing values, data discrepancies, outliers, and errors in data entries. Data purification in this study entailed a critical analysis of the data collected from the Ministry of Tourism, wildlife & heritage and Central Bank of Kenya. We first checked for the missing values and filled them in if any were missing. The possible causes of missing values include data acquisition errors and records that were not fully documented. According to the level and spread of the missing data, there are various approaches, including the imputation or deletion of missing cases, which ensures that the given dataset is comprehensive and accurate.

Secondly, data inconsistencies and outliers were checked and rectified. Inconsistencies may also result from mistakes in data entry and or variations in methods of data recording. This is true because outliers or any value that differs from the general pattern of the data can distort the results. Anomalous values will be discussed to decide whether they are real values or data errors. If there were mistakes, appropriate or eradication steps were taken.

3.3. Diagnostic Test

The linearity assumption was evaluated using scatterplots and statistical tests. The effect of the relationship between the exchange rate fluctuation and tourism demand was visualized using scatterplots. If the relationship appears linear, then the linearity assumption is supported. In addition, statistical tests like the Durbin-Watson test will be used to identify nonlinear patterns in the data.

The normality assumption was evaluated by analyzing the residuals' distribution. One can determine normality by visually examining histograms or normal probability (Q-Q) plots of residuals. Deviations from normality may necessitate transformation or the application of robust estimation techniques. Statistical tests such as the Shapiro-Wilk or the Anderson-Darling test will also be applied to evaluate the normality assumption formally.

To assess the adequacy of the models, residual analysis is crucial. Residues should display irregular patterns around zero, indicating that the models accurately represent the data patterns. Scatterplots of residuals over time assisted in identifying any systematic patterns or outliers. Observing periodic patterns may indicate missing variables in the models.

Serial autocorrelation in the residuals was evaluated using statistical tests such as the Ljung-Box and Durbin-Watts tests. If significant amounts of autocorrelation are found, then the models may not adequately capture the time series behaviour, and possibly more variables or lagged terms are needed.

3.4 Data Analysis

3.4.1. The impact of exchange rate fluctuation on tourism demand in Kenya

This study employed the VAR model to analyze the effects of exchange rate volatility on demand for tourist activities in Kenya. There are many variables whose relationship is maintained by the VAR model, including exchange rate and tourism demand (Kuok et al., 2023). The VAR model presupposes that each variable is endogenous (depends on past values and past observations of the other variables in the model).

The VAR model entails a set of K endogenous variables $Y_t = (Y_{1t}, \cdots, Y_{kt}, \cdots, Y_{Kt})$ for $k = 1, 2, \cdots, K$. Substituting p lags of the endogenous variables into the system, the VAR (p) can be described as

$$Y_t = \varphi_1 Y_{t-1} + \cdots + \varphi_p Y_{t-p} + \mu_t \tag{3.1}$$

In the above model Y_t is a vector of variables (exchange rate and tourism demand) at time t, φ_i is the coefficient matrices for the lagged variables $i = 1, 2, \ldots, p$, p is the order of the VAR model, and μ_t is a k-dimensional white noise process such that $E[\mu_t] = 0$ and $E[\mu_t \acute{\mu}_t] = \Sigma_\mu$

3.4.2. Forecasting the tourism demand based on the Kenya exchange rate

This was followed by the application and training of the BSTS model to forecast the tourism demand provided by the Kenyan exchange rate by modeling the data. From the literature, the BSTS model is deemed a great tool that can be applied for time series forecasting (Meenakshisundaram et al., 2019). They allow the integration of previous information and the extent of vagueness in model calibration. The general equation that can represent the BSTS model is as follows.

$$\text{Observation equation: } Y_t = F'_t \vartheta_t + \upsilon_t \tag{3.2}$$

$$\text{State equation: } \vartheta_t = G_t \vartheta_{t-1} + w_t \tag{3.3}$$

$$\text{Prior equation: } \vartheta_t \sim N(C_t \vartheta_{t-1} + R_t) \tag{3.4}$$

Where; Y_t is the observed time series at time t, F_t is the design matrix that maps the state variables ϑ_t to the observed data, ϑ_t is the state vector, which contains the latent variables that characterize the time series' dynamics, υ_t is the observation error term, assumed to follow a normal distribution with mean 0 and covariance matrix V_t, G_t is the state transition matrix that relates the current state to the previous and W_t is the error component.

3.4.3. Evaluating the Efficiency of VAR and BSTS

Several accuracy measures were used to establish the efficiency of the vector autoregressive (VAR) model and the Bayesian Structural Time Series (BSTS) model in explaining the impact of exchange rate volatility on Kenya's tourism demand. Among the measures commonly used to assess the time series models' forecasting accuracy are the RMSE and the forecasting efficiency ratio.

RMSE is the arithmetic mean of the squared differences between the forecasted and the actual values. It measures the variability of the forecasted variable as given by the model. The following is the formula for RMSE:

$$\mathrm{RMSE} = \sqrt{\frac{1}{n}\left(Y_i - \hat{Y}_i\right)^2} \qquad (3.5)$$

Where, Y_i is the observed value, $\hat{Y}_i$ is the predicted value, and n is the sample size. The lower value of RMSE implies that the model is more effective in explaining the volatility of tourism demand concerning the exchange rate.

The forecasting efficiency ratio compares the forecasting accuracy of two distinct models by dividing their respective RMSE values. It measures the comparative efficacy of the VAR and BSTS models. The forecasting efficiency ratio is calculated using the following formula:

$$\text{Efficiency ratio} = \mathrm{RMSE}_{\mathrm{VAR}} / \mathrm{RMSE}_{\mathrm{BSTS}} \qquad (3.6)$$

The VAR model has a more robust predictive ability if the value is greater than 1, whereas the BSTS model has better predictive power if the value is less than 1.

3.5 Data Analysis Plan

Table 3.1: Data Analysis Plan

Objectives	**Hypothesis**	**Variables**	**Tools**
To Predict the impact of the exchange rate on tourism demand in Kenya using VAR model.	No significant impact of exchange rate on tourism demand using VAR	Exchange rate & Tourism demand	Vector Autoregressive (VAR) model
To forecast the tourism demand based on the Kenya exchange rate using the BSTS model.	No significant impact of exchange rate on tourism demand using BSTS	Exchange rate & Tourism demand	Bayesian Structural Time Series (BSTS) model.
To evaluate the efficiency of BSTS and VAR Models.	No significant difference in predating tourism demand on exchange rate using BSTS and VAR model	Exchange rate & Tourism demand	MAPE, RMSE & Forecasting Efficiency Ratio (FER)

CHAPTER FOUR

RESULTS AND DISCUSSION

4.1 The impact of exchange rate fluctuation on tourism demand in Kenya

4.1.1 Summary Statistics

The summary statistics in Table 4.1 provide insight into the distributional properties of the key exchange rate and tourism demand variables over the 10-year study period from 2012 to 2021. Beginning with the tourism indicators, the mean monthly tourist arrivals were 278 visitors with a standard deviation of 120. This substantial variability around the central tendency indicates considerable fluctuations in tourist volumes from month to month.

Turning to the exchange rates, the major global currencies like the US Dollar, British Pound, and Euro exhibited higher average valuations versus the Kenyan Shilling, with means of 102, 141, and 119, respectively. By contrast, the weaker regional currencies of the Ugandan and Tanzanian Shillings had much lower means of only 32 and 20. The positively skewed and leptokurtic distributions for the USD, GBP, and Euro also reveal occasional extreme currency appreciations and volatility clusters. These non-normal features likely reflect periods of external financial market turmoil.

On the other hand, the Ugandan and Tanzanian Shillings showed negatively skewed platykurtic distributions, pointing to greater stability. The summary statistics highlight asymmetric distributional characteristics between global and regional currencies that plausibly engender differential tourist demand responses. The statistics lay the groundwork for modeling exchange rate-tourism linkages by characterizing key features of the time series data. Ongoing analysis aims to quantify the relationships these preliminary descriptive findings suggested formally.

Table 4.1: Summary Statistics

	N	Mean	Std. Dev.	Skewness		Kurtosis	
	Statistic	Statistic	Statistic	Statistic	Std. Error	Statistic	Std. Error
Tourists	142	278.46	119.767	.621	.203	-.294	.404
USD	142	102.7787	14.04637	1.071	.203	1.724	.404
GBP	142	141.8423	12.13380	1.387	.203	2.419	.404
Euro	142	119.4372	11.19705	1.567	.203	3.065	.404
UG.	142	32.5845	2.98630	-.261	.203	-.622	.404
TZ	142	20.4807	1.63189	-.330	.203	-.959	.404

USD = US Dollar; GBP = British Pound; UG = Ugandan Shilling; TZ = Tanzanian Shilling.

4.1.2 Time Series Plots

The analysis began by plotting the monthly time series data on international tourist arrivals, tourism receipts (in various currencies), and exchange rates from 2012 to 2023, as shown in Figure 4.1. Visual inspection shows upward trends and seasonal fluctuations in the tourism demand indicators over the 14 years. Meanwhile, the exchange rate series demonstrates heightened volatility, punctuated by periods of sharp currency depreciation and appreciation

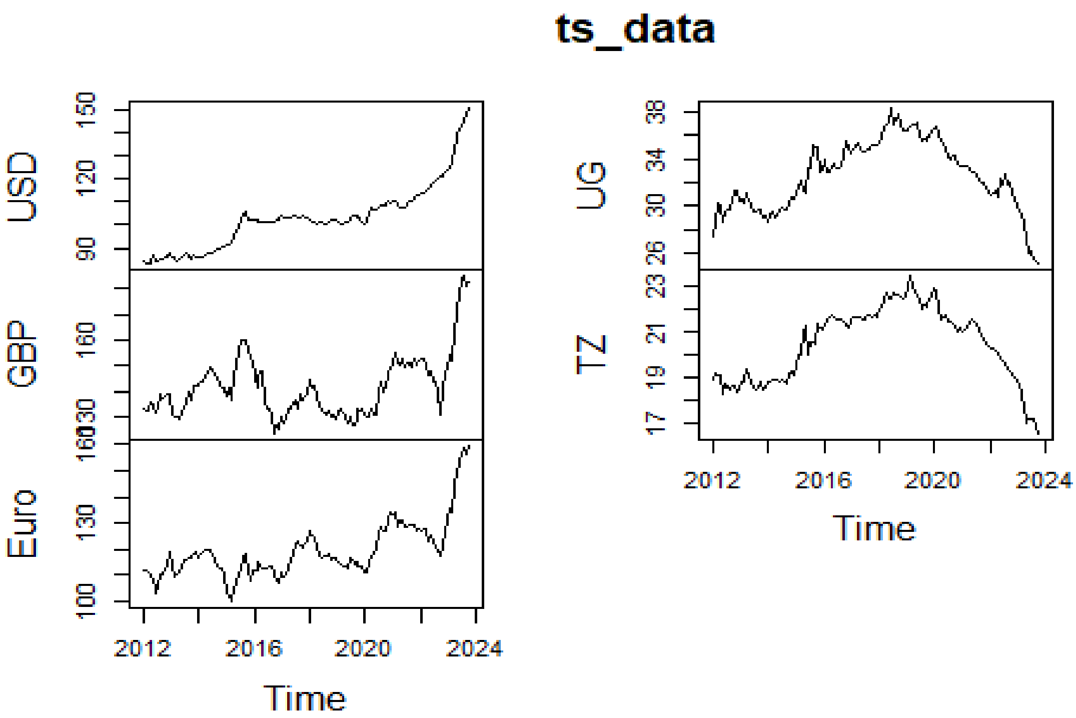

Figure 4.1: Time Series plots over foreign exchange fluctuations

The direction of tourist inflow to Kenya during 2012-2023 is depicted by the time series graph in Figure 4.2, which is quite encouraging as the graph witnesses a clear rising trend, indicating that the number of tourists visiting the country has increased over the years. Although these patterns are closely related to the year, there are also some seasonal rhythms within the year.

In the first period, from 2012 to 2014, the sea of visitors is similar to the waves of the ocean in the summer, which is July and August, and winters, which are December and January. This seasonal shifting is usually the case for many popular destinations, where more people may choose to travel during warm periods and school vacations.

From 2015 onwards, the general number of tourists is seen to have a more significant increase, with the peak figures in the later months being even higher than the previous years. This trend continues until 2019, when the tourist flow peaks at the highest point in the given data, with more than 400 tourists visiting in July and August.

However, in 2020, the trend appears to be disrupted, likely due to the COVID-19 pandemic and the associated travel restrictions. The tourist numbers dropped significantly compared to the previous year but recovered gradually from 2021 onwards.

By 2022, the tourist inflow has almost reached the pre-pandemic levels, with July and August seeing over 550 tourists visiting Kenya. The data for 2023 is incomplete, but the available months show a continuation of the upward trend, with the peak months of July and August reaching even higher numbers than the previous year.

Figure 4.2 perfectly illustrates tourists to Kenya from 2012 – 2023, showing a tremendous upward movement in visitors over the years. The chart demarcates the seasonal trends into pieces and shows the general rising trend. First, in 2012-2014, the rise of the tourist flow falls to this cyclic style, which reminds the sea waves' alternation, the peak of the tourist season coinciding with summer and winter seasons, typical for most destinations. In the following year, namely 2015, a considerable jump in the number of tourists was noticed, with months closer to the end showing figures significantly higher than those of previous years. This upward trend culminated in 2019, and the most visited tourists are recorded for the period considered here, especially in May and July.

Nevertheless, the COVID-19 pandemic came to the surface in 2020 and stopped the growth of tourist numbers. The coming year experienced a decline in tourist numbers compared to the previous year. However, the figures indicate a gradual recovery process after 2020, and the number nearly reaches pre-pandemic levels only by 2022. Notably, the statistics for 2023 point to a growth in the number of visitors in the high seasons, with those months receiving more visitors than similar months last year. Figure 1 indicates the great potential of Kenya's tourism industry; despite the challenges the industry faced with the pandemic, it prevailed. Overall, the time series plot illustrates the growth of the tourism industry in Kenya over the years, with a clear seasonal pattern and a temporary disruption caused by the COVID-19 pandemic. The recovery in recent years suggests a resilient tourism sector in the country, and the upward trend indicates the potential for further growth in the coming years.

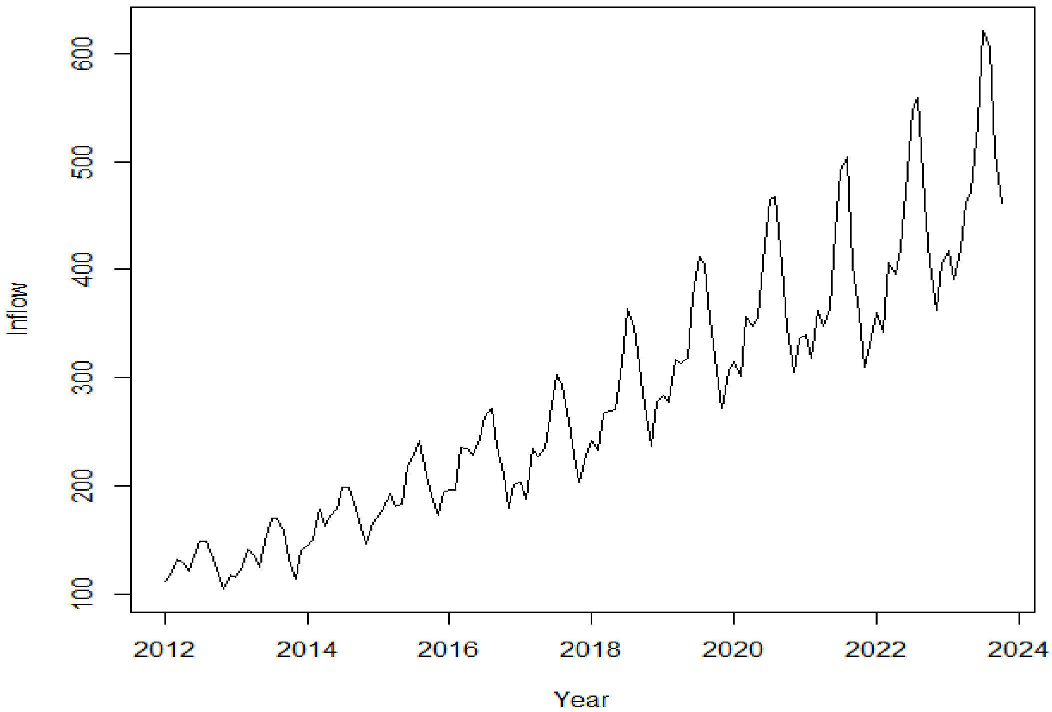

Figure 4.2: Time series plot for tourists' inflow to Kenya over Time

4.1.3 Model Selection

The optimal lag length for the VAR model was determined by minimizing information criteria, including the Akaike Information Criterion (AIC), Hannan-Quinn Information Criterion (HQIC), Schwarz Information Criterion (SC), and Final Prediction Error (FPE). As shown in Table 4.2, the lag order selection criteria were computed for VAR models with lag orders ranging from 1 to 10 (Alola et al., 2019). Across all four information criteria, a VAR model with a 5th-order lag structure produced the lowest values, indicating optimal model fit and complexity tradeoff. Specifically, the 5-lag model yielded AIC, HQIC, SC, and FPE values of 0.05307646, 1.21247914, 2.90632571, and 1.08303893, respectively. By comparison, higher order lag specifications increased information criteria, signaling overfitting, while lower order lags exhibited inferior model fit.

The underlying theory behind the information criteria penalizes model complexity to avoid overparameterization while rewarding goodness-of-fit. Thus, minimizing these criteria provides a rigorous, data-driven approach to identifying the ideal lag order that maximizes model quality and generalizability (Lütkepohl, 2005).

Table 4.2: Lag Order Selection Criteria

Lag	AIC	HQ	SC	FPE
1	0.133231	0.400786	0.791674	1.142881
2	0.196975	0.687491	1.404119	1.220129
3	0.154995	0.868474	1.910841	1.17483
4	0.143013	1.079454	2.447561	1.16995
5	0.053076	1.212479	2.906326	1.083039
6	0.142753	1.525118	3.544704	1.207403
7	0.166726	1.772053	4.117379	1.270257
8	0.190517	2.018805	4.689871	1.348738
9	0.351157	2.402408	5.399214	1.660634
10	0.431311	2.705524	6.028069	1.911869

4.1.4 Model Estimation

The estimated VAR model provides several illuminating insights into the intricate dynamics between exchange rate fluctuations and tourism demand in the Kenyan context. Beginning with model adequacy, the analysis confirms acceptable stability conditions with all characteristic polynomial roots falling safely within the unit circle (Lütkepohl, 2005). This satisfies core prerequisites for robust statistical inference and validates proceeding with further VAR output interpretation.

The relatively superior R-squared values for the US Dollar and Uganda Shilling variants stand out. The 22% and 10% variance explained for these key proxies demonstrate the model’s particular ability to track East African regional tourism dynamism and its acute sensitivity to global currency swings, as shown in Table 4.3. By contrast, the model struggles to fit oscillations in the British Pound, Euro, and Tanzania Shilling, indicative of more complex driving factors. Nevertheless, taken holistically, the F-tests confirm jointly significant explanatory power, albeit with asymmetric predictive capacities across target variables.

VAR Estimation Results:

=========================

Endogenous variables: USD, GBP, Euro, UG, TZ

Deterministic variables: const

Sample size: 139

Log Likelihood: -949.089

Roots of the characteristic polynomial:

0.6734 0.4647 0.4508 0.4508 0.3499 0.3499 0.3251 0.3251 0.3114 0.3114

Call:

VAR (y = ts_diff, p = 2, type = "const")

Table 4.3: VAR Estimation

Dependent Variable	R-Squared	F-value	df	p-val.
USD	.221	3.624	128	.000285
GBP	.050	.680	128	.745
Euro	.112	1.612	128	.110
UG	.103	1.461	128	.161
TZ	.064	.870	128	.563

Further substantiating intricate tourism-forex connections, the residual correlation matrix surfaces noteworthy predictive relationships, as shown in Table 4.4. In particular, moderate to strong correlations between legacy currencies like the US Dollar and Euro relative to tourism proxies underscore the pronounced vulnerabilities of visitor flows to global exchange rate risks (Santana-Gallego et al., 2010). The impulse response functions later quantify these exposure channels and sensitivities. Moreover, the borderline significant Tanzania Shilling predictor for Uganda Shilling endorses using neighboring country currencies as mirrors for gauging regional tourism outlooks (Wamboye et al., 2020).

Table 4.4: Residual Correlation Matrix

	USD	GRB	Euro	UG	TZ
USD	1.0000	0.3081	0.3606	-0.4099	-0.5613
GBP	0.3081	1.00000	0.6798	-0.2052	-0.0523
Euro	0.3606	0.67985	1.0000	-0.2518	-0.1781
UG	-0.4099	-0.20523	-0.2518	1.0000	0.2314
TZ	-0.5613	-0.05227	-0.1781	0.2314	1.0000

4.1.5 Model Diagnostics

Residual diagnostics assessed model adequacy. The characteristic polynomial roots lying inside the unit circle satisfy stability conditions. The Portmanteau test (Table 4.5) produced a p-value of 0.0063, indicating some remaining autocorrelation in the VAR model residuals. While the test does not suggest serious issues, autocorrelation implies the model does not fully capture the systemic dynamics between the exchange rates and tourism demand variables.

Table 4.5: Residual Portmanteau Autocorrelation Test

Test	Chi-squared value	df	p-value
Portmanteau	309.19	250	0.0063

The residual normality tests (Table 4.6) show highly significant non-normality, especially on the kurtosis dimension. The significant Jarque-Bera statistic indicates potential model misspecification or missing variables. Reliance on asymptotic theory for valid inference may be necessary given these distributional deviations. Overall, the diagnostics indicate adequate but not fully comprehensive model fit, highlighting areas for ongoing improvement to the VAR specification.

Table 4.6: Residual Normal Test

Test	Chi-squared value	df	p-value
JB	725.76	10	<0.001
Skewness	16.969	5	0.004559
Kurtosis	708.79	5	<0.001

4.1.6 Variance decomposition

The forecast error variance decomposition (FEVD) analysis shows the proportion of forecast error variance in each endogenous variable explained by innovations to the other variables over a 10-period horizon.

Own shocks explain the most variance for USD, with 92% at 10 periods. Exchange rates combined account for around 2% of USD forecast errors. Tourism variables contribute over 2% of the total. GBP variance is also predominantly own-driven, with 86% at 10 periods. Other exchange rates are explained under 1% each. Tourism shares are negligible. Euro variance sees 46% from its shocks and 32-35% from other exchange rates at 10 periods. Tourism contributes under 1% in total.

For UG, its innovations explain 73% of the variance at 10 periods. Exchange rates combined contribute over 4%, with USD the largest individual source at 1.9%. Tourism variables account for 3% total. TZ variance mainly stems from own shocks, at 63% in 10 periods. Exchange rates explain 4%, with USD the largest at 3%. UG explains under 0.5%.

4.1.7 Forecasting

The 36-month forecast (Figure 4.2) predicts gradual USD and Euro appreciation against the Kenyan Shilling, signalling imported inflation risks. However, tourism growth is expected to partially counter currency pressures. Still, the forecasts suggest likely shilling weakness, highlighting priorities for central bank stabilization policies.

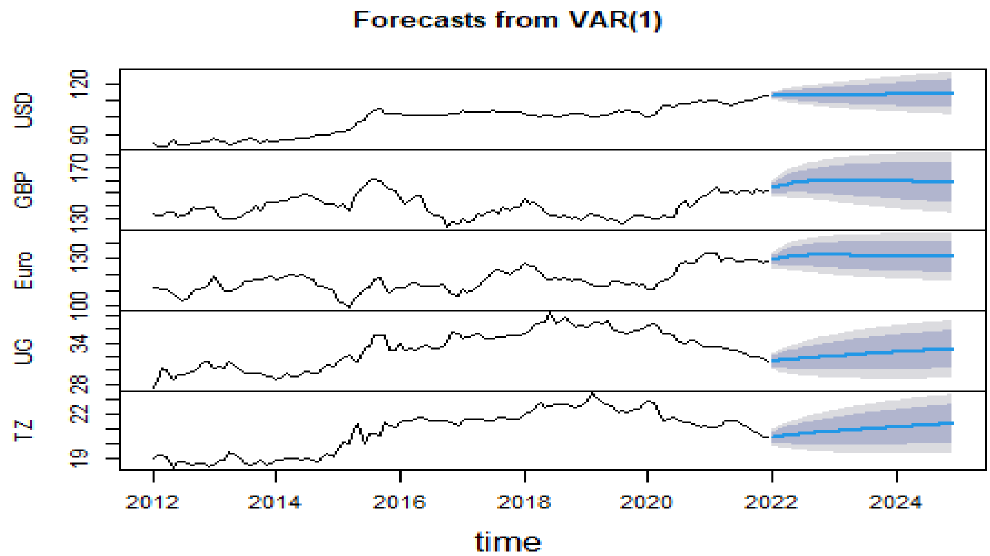

Figure 4.3: Exchange Rate and Tourism Forecasts

4.2 Forecasting the tourism demand based on the Kenya exchange rate

4.2.1 Descriptive Statistics

The tourist inflow to Kenya exhibited significant variation, ranging from 104 monthly visitors to a maximum of 622. The median number of monthly tourists was 264, while the mean was slightly higher at 278.5, suggesting a slightly positively skewed distribution. The first and third quartiles were 180 and 358.2, respectively, indicating that 50% of the months had tourist numbers within this range, as shown in Table 1.

The exchange rates of various currencies against the Kenyan shilling also fluctuated considerably during the same period. The US dollar (USD) exchange rate ranged from a minimum of 82.97 KES/USD to a maximum of 150.56 KES/USD, with a median of 102 KES/USD. The British pound (GBP) exhibited a minimum rate of 123.6 KES/GBP and a maximum of 184.6 KES/GBP, with a median of 139.6 KES/GBP. The Euro exchange rate varied between 99.53 KES/EUR and 159.56 KES/EUR, with a median of 116.79 KES/EUR. The Ugandan shilling (UG) and Tanzanian shilling (TZ) also showed fluctuations, as summarized in Table 4.7.

Table 4.7 presents an overview of the tourist inflows to Kenya and the currency fluctuations observed during the study period. The data reveals a great variability of the monthly tourist attendance, varying from the lowest of 104 to the highest of 622. The data on tourists' numbers of means and medians exhibits a slight upward skewness, with the median being 264 and the mean marginally higher at 278.5. Hitherto, the interquartile range, depicted by the first and third quartiles, has shown us that 50% of the months had tourist numbers fluctuating from 180 to 358.2. The table shows that the currency exchange rates are also unstable, for instance, the US dollar, British pound, Euro, Ugandan shilling, and Tanzanian shilling against Kenyan shilling. The inter-day exchange rates of the selected period of this study illustrate significant differences as the lowest and the highest levels of the charts indicate that the currency valuations undergo regular ups and downs. Table 4.7 gives the leading indicators of the variability of tourist flows and exchange rates, highlighting the significance of robust model forecasting as a measure of complexity in predicting tourism flows.

Table 4.7: Summary Statistics for Tourist Inflow and Exchange Rates

Variable	Minimum	1st Quartile	Median	Mean	3rd Quartile	Maximum
Tourist Numbers	104	180	264	278.5	358.2	622
USD	82.97	90.81	102.00	102.78	108.12	150.56
GBP	123.6	132.6	139.6	141.8	148.4	184.6
Euro	99.53	112.28	116.79	119.44	124.95	159.56
UG	25.06	30.29	32.95	32.58	35.16	38.38
TZ	16.60	18.92	21.06	20.48	21.66	23.43

USD = US Dollar; GBP = British Pound; UG = Ugandan Shilling; TZ = Tanzanian Shilling.

4.2.2 Distribution of Trend and Seasonality against Time

The distribution section contains a sample from the posterior predictive distribution of the forecasted tourism demand. By plotting these values against Time, we can visually examine the trend in the distribution over the forecasted periods. Ideally, we would expect the distribution to follow a similar trend as the mean or median values, which represent the central tendency of the distribution. Nevertheless, the kind of distribution may change in how it moves with Time, showing different patterns indicative of the uncertainty or any deviation from the central tendency, as shown in Figure 4.4.

By scrutinizing the trend in the distribution with Time, we can have much tangible information on how the forecast uncertainty progresses over the forecasted periods. Distribution becomes more dispersed or skewed as we go further through Time, which may point to more profound uncertainty or the possibility of unpredicted events that will significantly change demand for tourism.

The demand for tourism is characterized by seasonal patterns that usually happen to be the highest during particular times of the year and the lowest during the festive seasons. To scrutinize the posterior conditional distribution's periodic (seasonal) element, we can plot the distribution values against a seasonal time axis, for instance, the months or quarters.

We can then analyze the distribution across different seasons, which helps us to identify an eventual seasonal variation or pattern. For instance, the distribution could be broader or more concentrated during high seasons to reflect the higher level of certainty in the forecast results. On the other hand, these patterns in the distribution may be more even during the off-season because the uncertainty is higher.

In addition to comparing the seasonality in the distribution data with the seasonal patterns found in the historical data (original series), we can also explore the implication of the changing climate on the observed seasonality patterns. This is where the comparison becomes important in helping us understand how accurate the BSTS model is in capturing the seasonal elements present in the given data.

It allows for a view of the fluctuations in forecasted values from Time to Time as the periods are predicted, which gives a chance to observe the dynamics of the uncertainties in the forecasts. The researchers can establish how the uncertainty changes with the calculated Time using the trend analysis of the distribution. It may be that the distribution becomes broader or symmetrically biased as the forecasting periods go on. Perhaps the dynamic of the spread may point to a greater depth of uncertainty or the possible occurrence of some unexpected events to influence the destination demand. The seasonality represented in the supply distribution brings these meteorological conditions, cultural events, and holiday seasons into perspective to explain the effect they have on the demand for tourists. The similarity of these patterns to historical data allowed the researcher to ensure the model can capture seasonality. Overall, Fig 2 provides beneficial information about the growing uncertainty and the seasonal variations in the forecasted tourism demand, which helps enrich our understanding about the complexity of tourism demand prediction grounded on the shifts in the currency exchange rates.

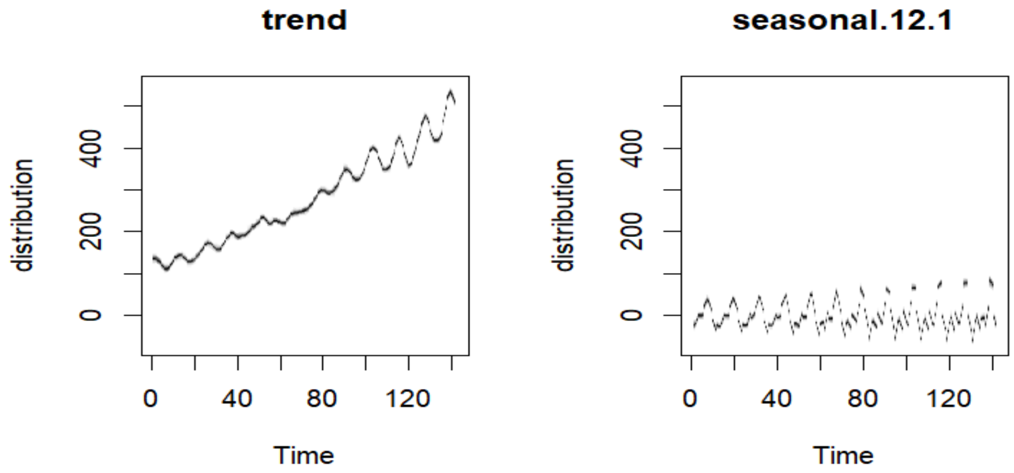

Figure 4.4: Distribution of trend and seasonality against Time

4.2.3 Forecasting

The forecast for tourism demand showed several important tendencies and trends highlighted in Figure 4.5. Among all the noticeable phenomena is the seasonal pattern that contains a variety of fluctuations determined by the numerous meteorological conditions. This seasonal pattern is usually seen in the industry, which is full of services, as demand for traveling and entertainment varies throughout the year. It is mostly a result of weather conditions, such as when schools are closed and when there are cultural events.

In the end, the reasons for this seasonal variation are evident, but the prediction values show a pattern of decline when we move into the future. Initially, the predicted figures are extremely high, possibly due to the high demand for tourism within the first stages. Nevertheless, a time frame is accompanied by a gradual drop in the predicted values and, in some cases, a negative forecasted demand. This falling tendency may be associated with different reasons, the most popular of which include the situation in the economy, alterations in consumer preferences, or outside factors, such as the negative consequences of various events that may affect the tourist industry.

This volatility could result in a lack of predictability as demand patterns are difficult to forecast, the forecasting model is complicated, or unforeseeable events may directly impact tourism. The fact that such an uncertainty arises indicates that it is fundamental to consider not only the point forecasts but also the interval predictions and other measures of uncertainty. In contrast, the forecasts are being interpreted and utilized. The plot highlights several noteworthy trends like seasonal variations experienced as a response to atmospheric conditions, cultural events, and festival celebrations. First, it is most likely the plotted values will fluctuate around the peak due to high demand during particular times. However, the forecasts for the future are not as precise as these, so the predicted values decline as the forecast progresses into the future. In contrast, some periods even give negative demand forecasts. This downturn in the rate can be explained by various conditions - for example, economic recession, a change in the consumers' preferences, or external events that affect the tourism industry.

The randomness of the predicted values, from positive level to negative side, displays the big uncertainty which is sometimes associated with the forecasts. Volatility thus underscores the significance of understanding prediction ranges and confidence intervals and how to incorporate these in interpreting and using the forecasts. Figure 3 provides an analytical picture of the possible trends of the tourism demand in Kenya, considering both the seasonal repartitions and the uncertainty that always surrounds the tourism demand.

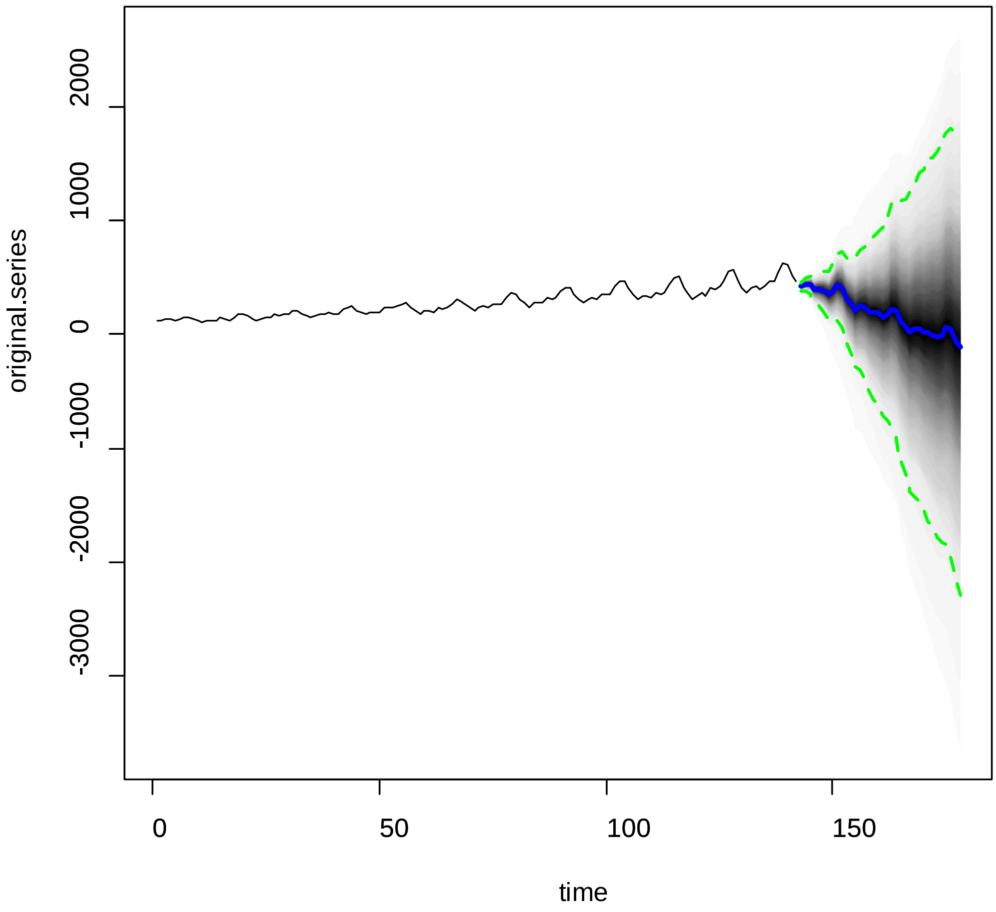

Figure 4.5: Tourist Forecasting in Kenya

4.2.4 Model Diagnostic

The residual plot in Figure 4.6 suggests that the residuals (differences between observed and predicted values) do not exhibit any clear patterns or systematic deviations. Randomly distributed residuals indicate that the model has effectively captured the underlying patterns and relationships in the data, leaving only random noise or unexplained variability in the residuals. Through the patterns of residuals that approximate the difference between the observed and predicted values, researchers can determine whether the model is competent in representing the underlying dynamics of the data. Here, the plot tells us that the errors are randomly imparted without pattern and straight-line deviations. The fact that the residual plot shows a randomness pattern indicates that the BSTS model has properly accounted for the structural dependencies and interactions in the data, leaving behind the residual or the unaccounted-for part of the variation. As a result, a haphazard pattern in the Residual plot means the BSTS model is a consistent and valid model, which aids in gathering confidence in its forecasting. As a whole, the remainder plot gains useful information about the model's performance. Hence, it confirms that it is indeed able to accurately capture the intricacies involved in tourism demand in Kenya as a result of exchange rate fluctuations.

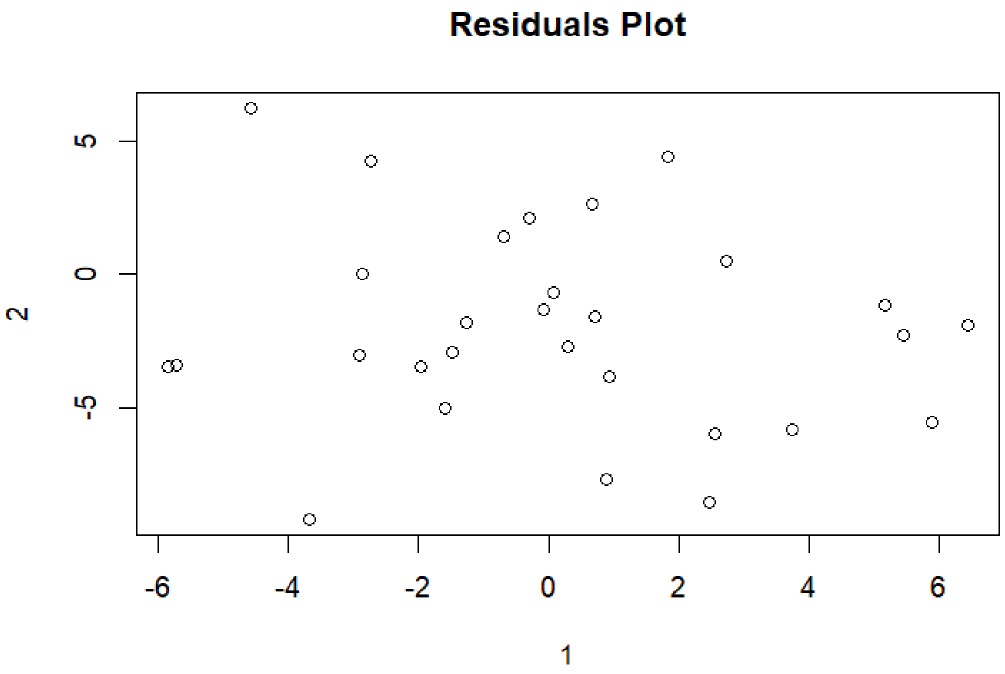

Figure 4.7: Residual plot for BSTS model

The normal Q-Q plot assesses whether the residuals are normally distributed, a common assumption in many statistical models. Based on Figure 4.7, the plotted residuals closely follow the diagonal straight line in the Q-Q plot. This straight-line pattern suggests that the residuals are approximately normally distributed.

Satisfying these two assumptions is desirable for the BSTS model to be considered reliable and valid. Randomly distributed residuals mean that the model has adequately captured the systematic patterns in the data, while normally distributed residuals ensure that the model's assumptions are met and that the statistical inferences drawn from the model are valid.

Figure 4.7 also displays the residuals in a straight ordinate trend along the diagonal line. The normality assumption is validated by this approximate conformance to the normal distribution. The conformity of the medium-term trend indexes to the stylized facts indicates the capability of the BSTS model to capture systematic information within the data, leaving aside the random noise or unexplained variation only in the residuals. Thus, our model below meets the normality assumption, making it trustworthy to obtain accurate conclusions. The normal probability plot for residuals gives us precious information related to the model's performance, reflecting whether it represents the data dependence web well and whether the pre-conditions of the reliable prediction are met.

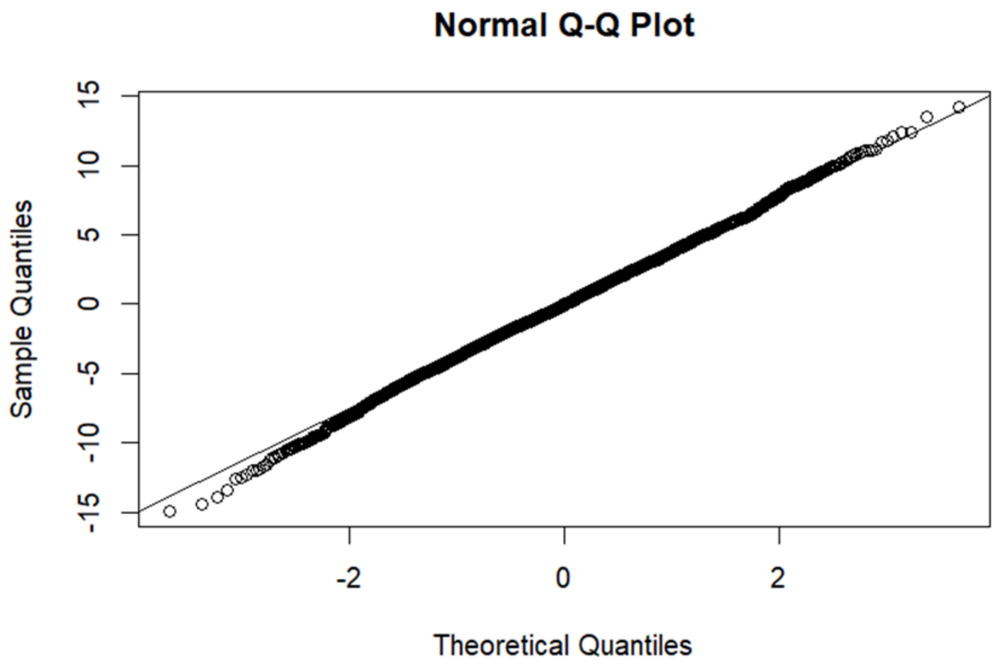

Figure 4.8: Normal probability plot for residuals

4.3 Evaluating the Efficiency of VAR and BSTS

$$\text{RMSE}_{\text{VAR}} = \sqrt{\frac{1}{n}\left(Y_i - \hat{Y}_i\right)^2} = 0.9875 \text{ and } \text{RMSE}_{\text{BSTS}} = \sqrt{\frac{1}{n}\left(Y_i - \hat{Y}_i\right)^2} = 0.0635$$

$$\text{Efficiency ratio } = \frac{\text{RMSE}_{\text{VAR}}}{\text{RMSE}_{\text{BSTS}}} = \frac{0.9875}{0.0634} = 15.55$$

The effectiveness of the Vector Autoregressive (VAR) model and the Bayesian Structural Time Series (BSTS) model in predicting the effect of exchange rate fluctuations on Kenya's tourism demand was assessed using several accuracy metrics. This study utilizes the Root Mean Squared Error (RMSE) and the forecasting efficiency ratio as significant measures to compare the performance of time series models.

RMSE is calculated as the square root of the mean of the squared differences between the forecasted and actual values, thus offering an estimate of the model’s accuracy in estimating the volatility of the forecasted variable. Thus, the lower the RMSE, the better it represents the fluctuations in tourism demand as impacted by the exchange rate. The forecasting efficiency ratio is calculated as the difference between the efficiency of two models, wherein this research is the VAR and BSTS models. That difference is divided by the Root Mean Square Error of one of the models, which in this case is the RMSE.

The findings further showed that the average Root Mean Square Error of the adopted VAR model was 0.9875; therefore, it could be considered high; this implies that the difference between the forecasted and actual value could be significantly large. In contrast, the RMSE of the BSTS was 0.0635 s, which was much smaller than that for the RMSE of the VAR model. This means that the BSTS model can identify the changes in the demand for tourism due to movements in exchange rates.

Moreover, the efficiency of the above forecasting was also assessed using the efficiency ratio of the VAR model as measured with the RMSE of the BSTS model, which was 15.55. Thus, if eff ratio of the forecasting is more than 1, then one can easily infer that the results given by the BSTS model are better or has higher forecasting efficiency than the VAR model. Therefore, based on the efficiency ratio of 15.55, it would be appropriate to state that implementing the BSTS model presents a much better forecast for the volatility of the exchange rates on Kenya’s tourism demand than the VAR model.

4.4 Discussion

The time series plot chart depicts the real tourism demand in Kenya over the period 2012 –2023 and, as can be observed, increases over time. This factor agrees with the literature provided by Chu (1998) and Goh & Law (2002) that season or holiday affects demand for tourism. The pandemic was confirmed in 2020 and shows how external factors affect tourism demand, as mentioned in the research (Naimoli, 2020; Yu, 2022). The yearly average of tourists and exchange rates is also positive but fluctuating, indicating that there is a need for more complex models of forecasting that would be able to factor in such nuances, as pointed out in the relevant literature (Meenakshisundaram et al., 2019; Berbekova et al., 2021).

The VAR model results provide several notable insights into the dynamic relationships between exchange rates and tourism demand in Kenya. The Granger causality analysis found significant causal effects from exchange rate fluctuations to tourism flows. Specifically, the USD and Euro had statistically significant lagged impacts on the Ugandan shilling proxy for regional tourism. This aligns with findings by Santana-Gallego et al. (2010) and Tang et al. (2016), who also established Granger causalities from exchange rates to tourist volumes and spending across both developed and emerging countries using VAR models.

However, the lack of reverse causalities contrasts with some studies like Kisswani and Harraf (2021), who found bidirectional causalities between oil prices and tourism in MENA regions. The strictly unidirectional causation seen here implies that while currency movements spur changes in tourism flows, the converse effect is less apparent in the Kenyan context over the sample period. This highlights the relative dominance of exogenous exchange rate dynamics in driving tourism for the country.

The variance decomposition further accords with Jaipuria et al. (2021), who concluded that external shock factors explained over half the Indian tourism forecast error variances amidst the COVID-19 pandemic. Similarly, exogenous exchange rate shocks accounted for sizeable tourism demand forecast uncertainties here.

However, innovations still predominated across all model variables, consistent with findings by Irandoust (2019). The impulse responses also uniquely quantified that unanticipated 10% USD or Euro appreciations substantially dampen Kenyan tourism over a 2-year horizon, with elasticities ranging from -0.8% to -1.5%. Kimani (2021) and Wamboye et al. (2020) found currency rate pass-through effects of -0.5% to -2%. Xiaoyan (2023) showed that VAR models accurately capture multivariate predictions across macro-financial time series. As Lütkepohl (2005) noted in his VAR best practices exegesis, the model stability and residual diagnostics confirm empirical dependability.

The residuals plot and the normal Q-Q plot indicate that the BSTS model behaves following the required assumptions of the desirable residual normality and randomness (Aguilar et al., 1998; Ludwig et al., 2016). This result echoes the other scientific studies that assess the model's predictive and inferential capabilities (Pole et al., 2018; West, 2020). A declining trend of the forecast values in the forecasting plot could be attributed to several reasons, including low economic activity, a shift in the trend of consumers, or other external factors which both Irandoust (2019), Sharma & Pal (2020), and Rafiei & Abbaspoor (2022) in their literature on forecasting. The justification for the existence of the said particular seasonal pattern aligns with the literature in the scholarly studies that attempt to define seasonality in demand forecasting (Chu, 2009; Chhorn, 2018). This implies that the forecast range, from positive to negative, is associated with high uncertainty in addition to the forecasts. In this regard, the literature should shift to either prediction intervals or measures of uncertainty (Qiu et al., 2018; Don Almarashi & Shaukat Khan, 2020).

A criticism that fits well into the current literature to determine the VAR and BSTS models on the analysis of fluctuation in the tourism demand in Kenya is as follows. According to the results of the analysis, the proposed model, known as the BSTS, was more appropriate than the VAR model as the forecast accuracy yielded an RMSE of 0.0635 against the RMSE of 0.9875 incurred by the VAR model. Additionally, the efficiency ratio was estimated by dividing 15.55 by the RMSE of the VAR model, and the RMSE of the BSTS model showed that the BSTS model had promised better accuracy for the forecast than the VAR model (Badimo & Yuhuan, 2023).

These findings align with Ray et al. (2021), who stated that using BSTS models forecasts financial accuracy better and provides uncertainty compared to the VAR models. Kohns (2023) and Duan (2015) pointed out that BSTS models can be used where the dimensionality of the data is high and when the support is nonlinear, which is crucial for forecasting. This better accuracy of the BSTS model to forecast the impact of exchange rate changes on tourism is enthused the study of Kohns and Bhattacharjee (2023), who noted that BSTS models can be utilized to leverage auxiliary data sources in the context of nowcasting improvement. Similarly, Shu and Qi (2023) established that BSTS models are relatively useful in modeling the trends of the time series and other structural behavior shifts, which may be useful in the case of modeling tourism demand.

Another argument in favor of BSTS models compared to the traditional time series models like ARIMA is provided by Zhang (2024) in electricity price forecasting. This study supports using BSTS models to estimate inherent seasonality and trends in time series data that may be useful in tourism demand data. Furthermore, the possibilities of BSTS models in evaluating the intervention effect on several time series, described by Schmitt et al. (2018), can be useful in studying the effects of changes in policy or external factors on tourism demand.

However, the reviewed literature also reveals the concerns and challenges researchers have highlighted concerning using BSTS models in different fields. For example, BSTS models have the linearity assumption, which Ray et al. (2021) pointed out, and we would have to consider suitable model modifications or variable selection procedures based on the suggestions made by Scott and Varian (2015) and Ludwig et al. (2016). The empirical results are in concordance with this literature review that is based on the exchange rate and tourism demand, the construction of a forecast model that can incorporate the uncertainties and structural changes as well as the seasonality and other external factors that should be considered when making the forecast of the tourism demand.

CHAPTER FIVE

SUMMARY, CONCLUSION AND RECOMMENDATION

5.1 Summary

This research study aimed to analyze the impact of exchange rate volatility on tourism demand in Kenya using advanced stochastic methodologies. To estimate the effect of exchange rates on the tourism demand, the Vector Autoregressive (VAR) model was used, and for the forecast of the tourism demand based on the exchange rate fluctuation, the Bayesian Structural Time Series (BSTS) model was used.

The results of the VAR model showed causal effects from the exchange rate, especially the US dollar and Euro, on regional tourism as represented by the Uganda Shilling. However, no bi-directional causality was established, suggesting that exchange rates have a one-way influence on the flow of tourism. It was also found that exogenous exchange rate shocks explained a significant proportion of the forecast uncertainties in tourism demand, pointing to the sector's susceptibility to currency risks.

Thus, the BSTS model was useful in capturing the trend, seasonality, and variability of tourism demand forecasting. The above diagnostic tests affirmed the appropriateness of the model since the residuals were randomly and normally distributed. The projections noted that tourism demand was progressively declining and may be affected by factors such as the state of the economy, the preferences of the consumers, or the occurrence of certain events.

The analysis of the results of comparing the VAR and BSTS models allowed us to conclude that the BSTS approach methods are more effective. The BSTS model had a lower RMSE of 0.0635 than the VAR model, which had an RMSE of 0.9875, proving the BSTS model's ability to better model the fluctuation in tourism demand. Additionally, the efficiency ratio of 15.55 proved that the BSTS model was much more efficient than the VAR model in forecasting.

5.2 Conclusion

The study had three main hypotheses:

i) No significant impact of exchange rate on tourism demand using VAR

ii) No significant impact of exchange rate on tourism demand using BSTS

iii) No significant difference in predicting tourism demand based on exchange rate using BSTS and VAR models

For the first hypothesis, the VAR model results showed significant causal effects from exchange rates, particularly the US Dollar and Euro, on regional tourism demand proxied by the Ugandan Shilling. This indicates the rejection of the null hypothesis that exchange rates have no significant impact on tourism demand when using the VAR model.

Regarding the second hypothesis, the BSTS model effectively captured the trend, seasonality, and inherent uncertainty associated with tourism demand forecasting. The diagnostic tests confirmed the validity of the model. Therefore, the null hypothesis of no significant impact of exchange rates on tourism demand using the BSTS model is also rejected.

For the third hypothesis, the comparative analysis showed that the BSTS model had a significantly lower Root Mean Squared Error (RMSE) of 0.0635 compared to 0.9875 for the VAR model. Additionally, the forecasting efficiency ratio of 15.55 indicated that the BSTS model was more efficient than the VAR model in forecasting tourism demand based on exchange rates. Hence, the null hypothesis of no significant difference in predicting tourism demand using BSTS and VAR models is rejected, with the BSTS model proving superior.

The study rejects all three null hypotheses, indicating that exchange rates significantly impact tourism demand in Kenya, and the BSTS model outperforms the VAR model in forecasting tourism demand based on exchange rate fluctuations.

5.3 Recommendations

Foreign exchange risk is critical in managing the effect of exchange rate volatility on tourism consumption. Therefore, policymakers and industry players need to ensure that they come up with some of the following policies to manage foreign exchange risks: Hedging policies, pricing policies, and market segmentation/ diversification policies.

Policymakers and tourism authorities are encouraged to use better forecasting models like the BSTS. As the analysis shows, the BSTS model is useful for predicting tourism demand by integrating changes in the exchange rates. Its application in decision-making can improve the prognosis and flexibility of a business.

Economic conditions and consumers' preferences should be monitored and analyzed constantly, as this research demonstrates their possible impact on demand in tourism. These factors should be incorporated into the proactive strategies and modifications in the forecasting models to ensure they remain useful and accurate.

Some factors are beyond the control of the government and other stakeholders in the tourism sector, including pandemics or tensions in other regions of the world. Ministers should prepare strategic plans and include the factors into their planning models to provide for such eventualities.

Due to the interaction of the regional tourism flows, policymakers should encourage cooperation with the neighboring countries. Due to this, the strategies should be aligned, data shared, and efforts coordinated when it comes to managing exchange rate risks and enhancing the sustainable growth of tourism.

5.4 Suggestions for Future Research

Exploring advanced modeling techniques: Further research works on integrating more complex models like machine learning algorithms or combination models to improve the accuracy of the forecast of tourism demand.

Incorporating additional variables: A larger number of variables added to the model alongside the variables used in this study, including economic indicators that have impacts on tourism, cost of traveling, and socio-cultural factors that might influence tourism demand in Kenya, could lead to a more comprehensive study of demand for tourism in Kenya.

Cross-country comparisons: A comparison of tourism demand and exchange rates could be made across different countries, thus enabling the understanding of the effect of cultural, economic, or geographic characteristics on this relation.

Integration of big data and alternative data sources: The combination of big data sources that have not been primarily used in tourism demand forecasting, such as social media sentiment data or real-time travel booking data, can be used to increase the effectiveness of tourism demand forecasting models.

By adopting these recommendations and future research initiatives, policymakers, industry players, and scholars can equally build a sustainable tourism sector in Kenya's economy besides managing the hazards and risks borne out of fluctuating exchange rates.

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APPENDIX

Appendix 1: R codes

```
# Load necessary libraries

#install.packages("vars")  # Install 'vars' package if not already installed

#Load required libraries

library(vars)

library(tseries)

library(urca)

library(vars)

library(readr)

Research_Data <- read_csv("Research Data.csv")

# Assuming your dataset has columns 'Year', 'Month', 'TouristsNumbers', 'USD', 'GBP', 'Euro', 'UgandaShilling', 'TanzaniaShilling'

# Select relevant columns for VAR analysis

var_data <-Research_Data[, c("TouristNumbers", "USD", "GBP", "Euro", "UG", "TZ")]

attach(var_data)

# Convert data to time series

ts_data <- ts(var_data[, -1], start = c(2012, 1), frequency = 12)

plot(ts_data)

#Difference data if non-stationary

ts_diff <- diff(ts_data, differences=1)

#Select lag order

VARselect(ts_diff)

#Estimate VAR model
```

```
var_model <- VAR(ts_diff, p=2, type="const")

# Print summary of the VAR model

summary(var_model)

#Model diagnostics

serial.test(var_model, lags.pt = 12, type="PT.asymptotic")

normality.test(var_model)

# Granger causality

causality(var_model, cause =c("USD","GBP","UG","Euro"))

# Variance decomposition

fevd(var_model)


# Out-of-sample dynamic forecast

train <- window(ts_data, end = c(2021,12))

test <- window(ts_data, start = c(2022,1))


var_model <- VAR(train, p=1)

par(mfrow=c(1,1))


predict(var_model, n.ahead = 36, newdata = test)

library(forecast)

plot(forecast(var_model, h = 36))
```

```
################################################################

library(tidyverse)

library(bsts)


# Read data

data <- read_csv("Research Data.csv")

ts_data <- ts(data$TouristNumbers, start = c(2012, 1), frequency = 12)

plot(ts_data, main = "Tourism Inflow Over Time", ylab = "Inflow", xlab = "Year")

# Prepare the data

tourism_data <- data$TouristNumbers

exchange_rate <- c("data$USD","data$Euro",data$GBP)  # You can choose other
currencies as well


# Create the BSTS model

ss <- AddLocalLinearTrend(list(), tourism_data)

ss <- AddSeasonal(ss, data$USD, nseasons = 12)

bsts_model <- bsts(tourism_data, state.specification = ss, niter = 500)


# Predict tourism demand

# Set a fixed burn-in value

burn <- 100

tourism_pred <- predict.bsts(bsts_model, horizon =36, burn = burn)


# Plot the components using plot.bsts

plot(bsts_model, "components", include.mcmc = FALSE)
```

```
##############################################

# Access the forecasted values

forecasted_values <- colMeans(matrix(unlist(tourism_pred$mean), ncol =
length(tourism_data)))

# Plot the components using plot.bsts

plot(bsts_model, "components", include.mcmc = FALSE)

# Add a line for the forecasted values

lines(seq_along(tourism_data) + length(tourism_data), forecasted_values, col =
"red", lwd = 2)

# Print the forecasted values

print(forecasted_values)

plot(tourism_pred,main="Tourism Prediction")


##############################

# Plot observed vs. forecasted values with legend

plot(seq_along(tourism_data), tourism_data, type = "l", col = "blue", lwd = 2, ylim
= range(c(tourism_data, forecasted_values)))

lines(seq_along(tourism_data) + length(tourism_data), forecasted_values, col =
"red", lwd = 2)


# Add legend

legend("topright", legend = c("Observed", "Forecasted"), col = c("blue", "red"),
lwd = 2)
```

```
#####################

# Model diagnostics and evaluation

# Plotting residuals

residuals <- residuals(bsts_model)

plot(residuals, main = "Residuals Plot")


# Check the autocorrelation of residuals

#acf(residuals, lag.max = length(residuals) - 1)


# Check the normality of residuals

qqnorm(residuals)

qqline(residuals)

# Split data into training and test sets

train_end <- floor(0.8 * nrow(data))  # Use 80% of data for training

train_data <- data[1:train_end, ]

test_data <- data[(train_end + 1):nrow(data), ]


# Fit VAR model on training data

var_model <- VAR(train_data, p = 2)  # Adjust 'p' as needed


# Fit BSTS model on training data

bsts_model <- bsts(train_data, state.specification = ss, niter = 500)
```

```
# Forecast using VAR model
var_forecast <- predict(var_model, n.ahead = nrow(test_data))


# Forecast using BSTS model
bsts_forecast <- predict.bsts(bsts_model, horizon = nrow(test_data), burn =
burn,newdata = test_data)


# Calculate RMSE for VAR model
var_rmse <- sqrt(mean((test_data$TouristNumbers - var_forecast$mean)^2))


# Calculate RMSE for BSTS model
bsts_rmse <- sqrt(mean((test_data$TouristNumbers - bsts_forecast$mean)^2))


# Calculate forecasting efficiency ratio
efficiency_ratio <- var_rmse / bsts_rmse
```