'Modelling' UK Tourism Demand using Fashion Retail Sales

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Abstract

The United Kingdom (UK) is a world-renowned fashion hub where the economic importance of the tourism sector was recording continuous growth prior to the pandemic. Interestingly, tourism shopping is widely experienced yet seldom discussed from a tourism demand forecasting context. Driven by the potential relevance of tourism shopping and hoping to motivate increased collaboration between the tourism and fashion industries, we analyse whether fashion retail sales can be a leading indicator for inbound tourism demand in the UK. Using the Multivariate Singular Spectrum Analysis leading indicator algorithm, we forecast UK tourism demand and compare the results with six benchmark forecasting models. We find statistically significant evidence for the existence of cross-sector relations between the UK's fashion and tourism industries.

Keywords: Leading indicators; tourist arrivals; fashion retail sales; Multivariate Singular Spectrum Analysis; UK.

1 Introduction

Shopping, which is closely associated with tourism demand, is considered as one of the earliest, most popular, and most important aspects of tourism (Timothy and Butler, 1995; Law and Au, 2000; Geuens et al., 2004; Correia and Kozak, 2016). To this end, the fashion tourist is an important link between the fashion industry and the global consumer (Varley et al., 2018) in a world where the combination of shopping and tourism is growing exponentially (Ambagtsheer, 2020). It began in 1855 when Thomas Cook organised the first pleasure excursion which included a guide to recommended shops abroad (Saayman and Saayman, 2012). Since then, tourism shopping has evolved and is now seen as a solution for revitalizing rural areas, declining resorts, and traditional urban centres (Jansen-Verbeke, 1998). Realising the importance of tourism shopping, in 2016, the luxury Hong Kong retailer Lane Crawford targeted the fashionable traveler by designing custom trips in collaboration with Luxe Guides whereby the customised city guides also included a range of merchandise that correlated with each destination (Varley et al., 2018; Kaiser, 2016). Today, shopping is an essential purpose of tourism (Timothy and Butler, 1995) and a key deciding factor when travellers choose a travel destination (Ambagtsheer, 2020).

Saayman and Saayman (2012, p. 1318) rely on Heung and Qu (1998) to define the concept of tourism shopping as *"the expenditure on goods purchased in a country, by international visitors, either for consumption in the place where it is bought or for export but not including expenditure on food, drink of grocery items"*. The importance of consumption and acquisition of material goods in modern society has lead to a surge in tourism shopping (Featherstone, 1991; Shields, 1992; Timothy and Butler, 1995) whilst price fluctuations in neighbouring countries add to this trend (Timothy and Butler, 1995) as access to pricing information is rapid and increasingly transparent.

Given this context, we seek to determine whether the effects of tourism shopping on the UK economy can be exploited to improve the accuracy of tourism demand forecasts. Research into tourism shopping remains at an early stage (Choi et al., 2016). The focus of tourism studies that deal with retailing and shopping have been associated with behaviours, motivations, spatial travel patterns, shopper typologies, purchase intent, authenticity of product and experience, and the production and consumption of handicrafts (Kim et al., 2011; Choi et al., 2016). However, evidence also indicates that tourism has a positive impact on retail, with 1/3rd or half of a tourist's total expenditure being spent on shopping (Gratton and Taylor, 1987; Littrell et al., 1994; Heung and Qu, 1998; Bojanic, 2011).

We are interested in the UK for several reasons. Owing to the pandemic, the total contribution of tourism to gross domestic product in the UK dropped by 62.3% in 2021 whilst international visitor spend fell by a massive 71.6% (World Travel & Tourism Council, 2021). However, prior to the pandemic, UK was recognized as a top 10 tourist destination in the world (World Tourism Organization, 2019) with 38 million international visitors in 2018 (GOV.UK, 2019). Recognising the importance of tourism to the economy, the UK government launched the 'Tourism Sector Deal' aimed at boosting productivity, workforce skills development, and enhancing the visitor offer (GOV.UK, 2019). Even though the pandemic disrupted plans, substantial recovery is expected by summer 2022 with official tourism forecasts for the coming year indicating tourism demand will increase to 24 million with a corresponding increase in spending at £19.2 billion (VisitBritain, 2021). Given the importance of tourism for reviving economies, the government has outlined a series of actions to promote tourism post-pandemic (Newson, 2021). Therefore, empirical research into improving the accuracy of tourism demand forecasts is timely as accurate forecasts are mandatory for planning, decision making, and productive allocation of scarce resources (Hassani et al. 2017).

Research indicates that fashion events can add value and recognition to host cities, but this opportunity is not properly valued by the tourism industry (Liberato et al., 2021). Therefore, deviating from mainstream tourism shopping research and hoping to exploit the fact that shopping is known to be a key pull factor that attracts tourists to some city destinations (Heung and Cheng, 2000; Choi et al., 2015), we propose the following:

Research Question*: Can UK's fashion retail sales be a leading indicator for forecasting tourism demand?*

A leading indicator is an economic variable that often foreshadows the future changes in some aggregate economic activity (Kulendran and Witt, 2003) such as inbound tourism demand. Here, we consider total retail sales volume from textile, clothing and footwear stores only as a proxy for the fashion industry and as a variable that captures the effects of tourism shopping. Accordingly, in what follows, we refer to total retail sales volume from textile, clothing and footwear stores as fashion retail sales.

We associate tourism shopping with the UK economy for the following reasons. First and foremost, apart from tourism, which is one of the most successful industries in the UK (Tourism Alliance, 2017), the country is also home to London, which the 'Global Fashion and Luxury City Index' ranks as the 4th most important fashion capital in the world (International Fashion Digital Automated Quantification, 2019) and houses iconic department stores such as Harrods (Timothy and Butler, 1995), Marks and Spencer, Fortnum & Mason, Selfridges, Harvey Nichols, and Liberty London. Accordingly, it is reasonable to assume that tourism shopping is likely to play a significant role within the UK tourism industry, because many tourists visit to benefit from access to the latest fashion trends (Sedghi, 2015). Secondly, VisitBritain (2015) reported that at least 57% of all visits to the UK in 2014 involved shopping, thereby evidencing the high popularity of this activity for overseas visitors, whilst 40.7% of inbound tourists in 2013 shopped for clothes or shoes (VisitBritain, 2014). Thirdly, 16 million tourists from outside the European Union visit UK annually to shop (Street, 2020). Therefore, it is likely that tourism shopping makes a significant contribution to the UK's fashion retail sales. This was evident during the pandemic with UK luxury brands revenues suffering from weaker tourism in certain regions (Bourke, 2021). Interestingly, there is evidence of clothing and footwear recording the highest expenditure through tourism shopping in other markets as well (see for example, Heung and Qu, 1998).

In addition, several other factors also motivate our interest in this research. First, the exploitation of leading indicators for tourism demand forecasting is a popular practice in tourism research (Zhang and Kulendran, 2016). Timothy and Butler (1995) argue, tourists are motivated to travel by their desire and necessity to shop, and in Europe, tourism shopping can be a key motivator underlying the decision to travel. If evidence shows that fashion retail sales is a leading indicator, then it could motivate stakeholders in fashion and tourism industries to cooperate and benefit from the competitive advantage offered by the UK as a fashion hub. Secondly, to the best of our knowledge, there are no studies which seek to exploit the relationship between tourism and fashion retail sales for improving forecasting accuracy. Finally, the UK high street is struggling with significant store closures, and uncertainty following Brexit (Business of Fashion, 2019) and the Covid-19 pandemic. Therefore, there is an increased need for co-operation between the tourism and retail industries (Heung and Qu, 1998) in the UK for maintaining the going-concern of both industries. This is because tourism is recognised as a source of revenue for most world cities (Rabbiosi, 2015) and can have positive spill-over effects on retail. Thus, we hope the findings of this research will motivate and foster increased co-operation and collaboration between UK tourism and fashion industries.

To respond to our research question, we rely on a time series analysis and forecasting technique called Multivariate Singular Spectrum Analysis (Sanei and Hassani, 2015), which is referred to as the multivariate model hereon. This technique is also popular for its filtering and signal extraction capabilities (Rodrigues and Mahmoudvand, 2018). The use of this model as a leading indicator algorithm was proposed by Silva et al. (2017). The forecasts are compared with several benchmark univariate forecasting models such as Seasonal Naive, Autoregressive Integrated Moving Average (ARIMA), Exponential Smoothing, Trigonometric Box-Cox ARMA Trend Seasonal Model, Singular Spectrum Analysis, and Neural Networks to further validate the findings.

The choice of this particular multivariate model is for several reasons relating to the data structure. If a time series is stationary, then its sample mean, variance and autocorrelation function will be constant over time (Chen et al., 2008). However, UK tourism demand and fashion retail sales (see Figure 2 in Section 3) show signs of structural breaks (caused by recessions and other economic disruptions) through the growth and declines which are visible in these series, and such breaks are known to make time series non-stationary (Hassani et al., 2014). Therefore, nonparametric forecasting techniques such as this multivariate model which are not restricted by the parametric assumptions of stationarity and normality can handle this data better (Silva et al., 2017). In addition, given the highly seasonal nature of both time series, models with filtering capabilities can be useful for extracting the seasonal fluctuations and reducing noise levels. Moreover, when modelling multiple time series, this method is advantageous as it considers the co-integration between time series and the forecasting performance of this model improves when there is dependency among time series (Rodrigues and Mahmoudvand, 2018). Accordingly, it is not the peaks (caused by holiday effects for example) that affect the modelling process but the dependency structure and the dynamical behaviour of the series which this multivariate model is very powerful at handling (please see, Hassani and Mahmoudvand (2015)). Finally, unlike with traditional time series methods, when using this multivariate model we do not need to impose systematic and deterministic patterns.

Overall, our study makes several contributions. First, we cater to the gap in tourism demand literature in terms of exploiting cross sector relations between tourism and the fashion industry for improving forecast accuracy by being the first academic study presenting empirical evidence for the relation between UK tourism demand and fashion retail sales. Second, we add to the list of factors that have been evaluated as potential leading indicators for improving tourism demand forecasts and thereby provide tourism forecasters with more choice. Finally, we present the most comprehensive forecast evaluation (covering both short and long run forecasts) of this multivariate model in tourism forecasting literature by comparing our findings against six benchmark forecasting techniques.

In what follows, Section 2 presents a concise review of literature exploiting leading indicators for improving tourism demand forecasting. Section 3 introduces the forecasting models used in this study. Section 4 presents the data and measures used for evaluating forecast accuracy. Section 5 reports the results following data analysis, and Section 6 presents a concise discussion. The paper concludes in Section 7.

2 Literature Review

Silva et al. (2017) presents a comprehensive review of research exploiting leading indicators to improve tourism demand forecasts up until 2016. As such, our review focuses on more recent research.

Silva et al. (2017) introduced a modified Multivariate Singular Spectrum algorithm for finding leading indicators and evidenced the existence of cross country relations that are useful for improving the accuracy of forecasts for European tourist arrivals. Onder (2017) used an Auto-Regressive Distributed Lag Model to determine whether Google Trends (web and image indices) can help improve tourism demand forecasts. The results showed that Google Trends web and/or image indices were best at improving the forecast accuracy for Vienna, followed by Belgium, Barcelona, and Austria. Cao et al. (2017) proposed the global Vector Autoregression approach to model tourism demand and showed that tourism demand in 24 major countries were dependent on shocks to China's tourism price and real income variables. Using an Auto-Regressive Distributed Lag Model in a destination–origin panel setup, Otrachshenko and Bosello (2017) showed that marine protected areas and the fraction of overexploited species significantly impact inbound coastal tourism.

Wan and Song (2018) estimated logistic models and found that leading indicators of Hong Kong's growth rate in tourism demand growth can also predict positive and negative states in the country's tourism demand. Adeola et al. (2018) used a Poisson regression to show that absence of violence and political stability, infrastructure, foreign direct investment, real exchange rate, taste formation, trade openness and per capita income are key drivers of tourism demand in Africa. Wang et al. (2018) used a linear regression model with panel data and transaction data from a leading Chinese online travel agent to show that local outbound tourism demand in China is significantly impacted by air quality in the place of origin. Ongan and Gozgor (2018) found a negative correlation between the number of tourist arrivals from Japan and the US

Economic Policy Uncertainty index when they applied a widely used demand analysis model on US inbound tourism demand from Japan.

Investigating the interdependency between tourism and the yield curve spread in the Spanish economy using a Dynamic Conditional Correlation Generalized Autoregressive Conditional Heteroskedasticity model led Santamaria and Filis (2019) to uncover that the tourism-expected economic growth relationship is time varying and volatile in sign and magnitude. Law et al. (2019) forecasted monthly Macau tourist arrival volumes using a deep learning approach to identify highly relevant features when faced with a large volume of search intensity indices. Their model outperformed support vector regression and artificial neural network models. Onder et al. (2019) used Mixed-data Sampling with sentiment of online news media as a leading indicator and showed that this model can outperform time-series and naive benchmarks. Assaf et al. (2019) forecasted international tourist arrivals in nine Southeast Asian countries using Bayesian global vector autoregressive modelling. They found that external shocks to a key economic variable in a given destination has spillover effects on the tourism demand in neighboring countries. Demir and Gozgor (2019) found that increased levels of press freedom promotes inbound tourism when they analysed tourism demand in 160 countries using the fixed-effects, the Hausman–Taylor, and the dynamic panel data estimation techniques.

Emili (2020) relied on Ordinary Least Squares estimations to determine whether web-traffic data and climate indicators could forecast monthly international tourism demand at the micro destination level. They found that Google Trends is an important short-term leading indicator for both arrivals and overnights. Using Granger causality tests and Auto-Regressive Distributed Lag Models, Onder et al. (2020) found that Facebook likes can be a leading indicator of tourism demand of Graz, Innsbruck, Salzburg, and Vienna. Mushtaq et al. (2020) found evidence for a link between institutional quality and international tourism demand of India when they employed a panel autoregressive distributed lag model with data from top 30 tourist originating countries for India.

Logistic regression was used by Ridderstaat (2021) to show that Net Financial Wealth is a determinant of tourism demand cycles. More recently, researchers have begun exploiting Big Data as leading indicators with several attempts at making use of freely accessible internet data. Those interested in a detailed review of studies using internet data for tourism forecasting are referred to Li et al. (2021). For example, Guizzardi (2021) analyse the value of a Big Data price index composed of best available rates published on Expedia.com as a leading indicator for tourism demand forecasting and find a Generalized Additive Model outperforming the alternatives considered in that study. Xie et al. (2021) proposed a least squares support vector regression model with gravitational search algorithm with search query data from Baidu and economic indexes as leading indicators to forecast tourism demand. Havranek and Zeynalov (2021) showed that weekly Google Trends data is a leading indicator for forecasting tourist arrivals in Prague using a Mixed-data Sampling forecasting model. Höpken et al. (2021) too exploited Google Trends data as a leading indicator for tourism demand forecasting within an Artificial Neural Network model to show that it outperforms forecasts from an Autoregressive Integrated Moving Average model.

Table 1 below summarises not only the methods used in the search for leading indicators within tourism demand but also the different variables that have been considered as leading indicators. As evident, there have been no attempts at evaluating fashion retail sales as a leading indicator for forecasting tourism demand. Accordingly, we hope our research will create the potential for developing stronger relations between the fashion and tourism industries in future.

Method	Variables	Author(s)
Cross Correlation	Income, Unemployment, Forward Exchange Rate, Money Supply, Price Ratio, Industrial Production, Imports and Exports	Turner et al. (1997)
Adjusted ARIMA	Economic Variables	Cho (2001)
Cross Correlation	Economic Activity, Prices, and Financial Activity	Rossello (2001)
Transfer Function	Relative Price, Nominal Exchange Rates, Adjusted Relative Price, Origin Country Real Disposable Income, and Origin Country Real Gross Domestic Product	Kulendran and Witt (2003)
Transfer Function	Gross Domestic Product, Exchange Rate, Share Price, Unemployment Rate, Exports, Imports, and Consumer Price Inflation	Kulendran and Wong (2009)
Panel Three-stage Least Squares	Consumer Expectations of Future Economy, Hours Worked in Paid Jobs, and Household Debt	Yap and Allen (2011)
Threshold Autoregression	Consumer Price Inflation	Che (2013)
Tinbergen Gravity Model	Gross Domestic Product, Paved Roads, Total Networks, Rail Lines, Air Transport, Common Language, Common Border, Distance, Room Availability	Kosnan et al. (2013)
Fixed-effects Panel Data	Political Instability, Heritage, and Terrorism	Yap and Saha (2013)
Structural Time Series	Business Sentiment Indicators	Guizzardi and Stacchini (2015)
Vector Error Correction Model, Error Correction Autoregressive Distributed Lag Model, Vector Autoregression, and Time Varying Parameter	Destination's Own Price, Price of Competing Destinations, and Tourist Income	Gunter and Onder (2015)
ARMAX and Regression Models	Google Trends and Baidu Index	Yang et al. (2015)
Autoregressive Mixed-data Sampling	Google Trends	Bangwayo-Skeete and Skeete (2015)
Granger Causality	Real Gross Domestic Product, Imports, and Gross Wages	Tica and Kozic (2015)
Ordinary Least Squares and Autoregressive Distributed Lag	Crime Rates	Mehmood et al. (2016)
Gravity Model	Cultural Variables and Climate Variables	Wang and Xi (2016)
Seasonal Autoregressive Moving Average with Exogenous Variables	Macroeconomic Variables	Chatziantoniou et al. (2016)
Euclidean Distance Statistics	Climate Variables	Zhang and Kulendran (2016)
Support Vector Regressions	Google Trends	Jackman and Naitram (2016)
World Gravity Model	Climate Variables	Pintassilgo et al. (2016)
Generalized Method of Moment	Gross Domestic Product per Capita, Cost of Travel, Indicator for Prices, Relative Tourist Price Index, Tourist Price Substitute, Number of Hotel Rooms, and Political Stability	Habibi (2017)
Multivariate Singular Spectrum Analysis	Tourist Arrivals from Other European Union Countries	Silva et al. (2017)
Auto-Regressive Distributed Lag Model	Google Trends (web and image indices)	Onder (2017)
Global Vector Autoregression	Tourism Price and Real Income Variables	Cao et al. (2017)
Auto-Regressive Distributed Lag Model	Marine Protected Areas and Fraction of Overexploited Species	Bosello (2017)
Logistic Models	Real Income, Tourism Price, Consumer Price Inflation, and Exchange Rates	Wan and Song (2018)
Poisson Regression	Absence of Violence, Political Stability, Infrastructure, Foreign Direct Investment, Real Exchange Rate, Taste Formation, Trade Openness, and Per Capita, and Income	Adeola et al. (2018)
Linear Regression	Air Quality	Wang et al. (2018)
Error Correction Model	Economic Policy Uncertainty index	Ongan and Gozgor (2018)

Dynamic Conditional Correlation Generalized Autoregressive Conditional Heteroskedasticity	Yield Curve Spread	Santamaria and Filis (2019)
Deep Learning	Search Intensity Indices	Law et al. (2019)
MIxed-DAta Sampling	Online News Media Sentiment	Onder et al. (2019)
Bayesian Global Vector Autoregression	Real Gross Domestic Product	Assaf et al. (2019)
Fixed-effects, and Dynamic Panel Data Estimation	Press Freedom	Demir and Gozgor (2019)
Ordinary Least Squares	Google Trends and Climate Indicators	Emili (2020)
Auto-Regressive Distributed Lag Model	Facebook Likes	Onder et al. (2020)
Panel Auto-Regressive Distributed Lag Model	Institutional Quality	Mushtaq et al. (2020)
Logistic Regression	Net Financial Wealth	Ridderstaat (2021)
Generalized Additive Model	Price Index	Guizzardi (2021)
Least Squares Support Vector Regression Model with Gravitational Search Algorithm	Search Query Data from Baidu and Economic Indexes	Xie et al. (2021)
Mixed-data Sampling	Weekly Google Trends Data	Havranek and Zeynalov (2021)
Artificial Neural Network	Google Trends	Höpken et al. (2021)

Table 1: Chronological summary of methods used for evaluation and variables considered as leading indicators in tourism demand literature.

3 Methodology

3.1 Horizontal Multivariate SSA (HMSSA) Algorithms

Singular Spectrum Analysis (SSA) is a noise filtering and forecasting technique (Broomhead and King, 1986a,b). In brief, the multivariate model can be defined as SSA applied to multiple time series (Rodrigues and Mahmoudvand, 2018). Whilst Silva at al. (2017) proposed the use of this multivariate model for identifying leading indicators in tourism demand forecasting, it is noteworthy that these forecasting algorithms have been applied in the past in various contexts for solving real world forecasting problems (see, for example, Mahmoudvand et al., 2019; Silva et al., 2018; Hassani et al., 2018; Mahmoudvand et al., 2017; Hassani and Mahmoudvand, 2015). Below, we summarise the multivariate modelling. Those interested in the detailed step-by-step algorithms are referred to Hassani and Mahmoudvand (2015) and Sanei and Hassani (2015) for the theoretical underpinning, and the Supplementary Data.

The performance of the multivariate model depends on the choices of window length L and number of eigenvalues r, and similarity and orthogonality among series play an important role (Hassani and Mahmoudvand, 2015). Here, the two trajectory matrices are organised in Horizontal form (Hassani and Mahmoudvand, 2015) and the algorithm generates the best possible multivariate forecast by minimising a loss function which enables identification of the optimal window length L and number of eigenvalues r.

The multivariate modelling process involves two main stages: decomposition and reconstruction, each with two corresponding steps: embedding, and singular value decomposition, and grouping, and diagonal averaging, respectively (see Figure 1). The decomposition stage takes a noisy time series and decomposes this into various components such as trend, oscillatory components, and structureless noise. This is made possible via the embedding step which maps a one dimensional time series into a multidimensional time series, resulting in a trajectory matrix. Here, it is noteworthy to point out that the time lag structure we impose on the time series (as our data is evaluated at lag 0, 3, 6, and 12) is handled within the embedding stage. Next, Singular Value Decomposition is applied on this trajectory matrix to obtain eigenvalues that capture all information contained within a given time series. Thereafter, we move to the reconstruction stage which distinguishes between signal and noisy components in order to generate a less noisy time series. The grouping step is used to group the signal components together whilst grouping the noisy components separately. Then, diagonal averaging is performed to obtain a less noisy time series which can be used for forecasting using the recurrent or vector forecasting algorithms as explained in the Supplementary Data.

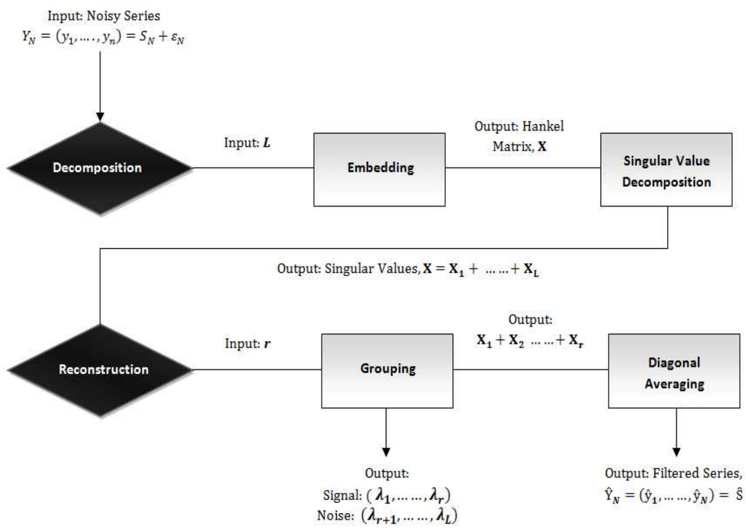

Figure 1: A summary of the basic Singular Spectrum Analysis process.

3.2 Benchmarks

All benchmarks models were estimated using the 'forecast package' (Hyndman and Khandakar, 2008) in *R*. The Seasonal Naive model is considered as it is useful for highly seasonal data (Hyndman and Athanasopoulos, 2021). The Autoregressive Integrated Moving Average algorithm (ARIMA) 'auto.arima' (Hyndman and Khandakar, 2008) was also used. ARIMA models have been used in tourism research since the 1970s and for tourism demand forecasting in the most recent decades (Guizzardi, 2021). Likewise, Exponential Smoothing is also an increasingly popular tourism forecasting model and we exploit the exponential smoothing algorithm in the forecast package that overcomes some limitations seen in previous exponential smoothing models (Makridakis et al., 1998). Hyndman and Athanasopoulos (2021) provides a detailed description of the theory underlying exponential smoothing. We also consider Neural Networks which is growing in popularity with the emergence of machine learning. We rely on the 'nnetar' algorithm made available via the forecast package (see, Hyndman and Athanasopoulos, 2021 for a detailed description). Next, we also exploit a model that was developed to provide more accurate forecasts when faced with complex seasonality, referred to as the Trigonometric Box-Cox ARMA Trend Seasonal Model, which is effectively an exponential smoothing state space model with Box-Cox transformation, ARMA error correction, Trend and Seasonal components (De Livera et al., 2011). Finally, we apply Singular Spectrum Analysis which is the univariate counterpart of the multivariate model used in this study (Hassani, 2007).

4 The Data and Metrics

4.1 The Data

The data was obtained via the Office for National Statistics in the UK and includes non-seasonally adjusted UK tourist arrivals and volume of non-seasonally adjusted total retail sales from textile, clothing and footwear stores from January 2004 to October 2019, $N = 190$. For the forecasting exercise, we adopted an expanding training sample with approximately 2/3rd of the data (January 2004 - June 2014) being used to train our models and the remaining 1/3rd (July 2014 - October 2019) as the test set. Figure 2 plots the time series for tourist arrivals and fashion retail sales in the UK. This shows clear signs of strong seasonality and a trend in the data. Pearsons correlation indicates a weak positive linear relationship ($r = 0.17$) between these two data sets which suggests the lack of a significant relationship worthy of investigation. However, Rodrigues and Mahdmoudvand (2018) evidence that it is co-integration and not correlation between time series that is important when modelling data using the multivariate model.

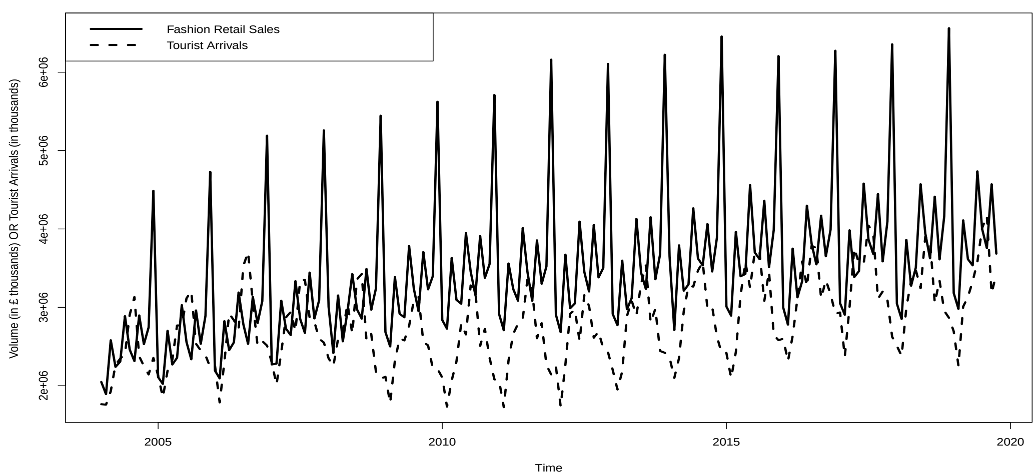

Figure 2: UK tourist arrivals and total retail sales volume (textile, clothing and footwear stores) from January 2004 - October 2019.

A closer analysis of the data via seasonal plots (Figure 3) show that fashion retail sales peak in December each year whilst tourism demand peaks in August except in 2010, 2011, 2012, 2015, 2016, 2017 and 2018 where the peaks have occurred in July. As such, it appears that Christmas is the most important period for fashion retail sales as opposed to Black Friday and other promotional periods whilst the warm weather in July and August appear to attract most tourists into the country. Thus, these series are affected by holidays and weather.

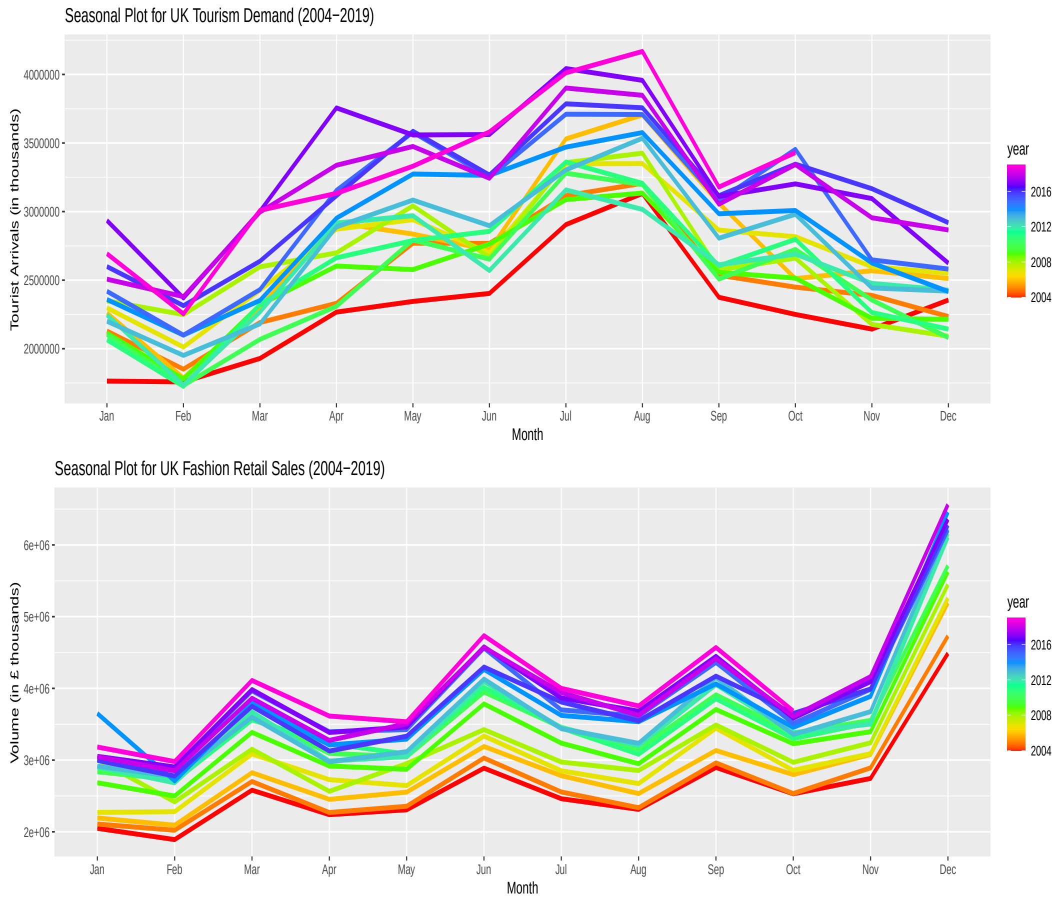

Figure 3: Seasonal plots for UK tourism demand and fashion retail sales.

Table 1 reports key descriptive statistics. Both time series are skewed, indicating that median values are more accurate measures of central tendency. As such, the median monthly arrivals of 2,709,500 and median monthly fashion retail sales at £3,334,073,000 are more accurate representations indicating that tourist arrivals and fashion retail sales were at or above these figures over 50% of the months considered here. The coefficient of variation shows that fashion retail sales have been comparatively more volatile than tourist arrivals into the UK. Finally, the Osborn, Chui, Smith, and Birchenhall test for Seasonal Unit Roots (Osborn et al. 1988) indicates that the fashion retail sales series has a seasonal unit root whilst the tourist arrivals series is not affected by a unit root problem. We also test the two time series for break points using the Bai and Perron (2003) test. This indicates that the tourist arrivals series was affected by a structural break in March 2015 whilst the fashion retail sales were affected by a structural break in August 2009.

Table 2: Descriptive statistics UK for tourist arrivals and fashion retail sales (Jan. 2004 - Oct. 2019).

	Mean	Med.	SD	IQR	CV	SW (p)	OCSB	Structural Breaks
Tourist Arrivals	2775021	2709500	536808	795000	19%	0.04	0	2015(3)
Fashion Retail Sales	£3459554	£3334073	£910339	£913264	26%	<0.01	1	2009(8)

Note: Med. - Median. SD - standard deviation. IQR - interquartile range. CV - coefficient of variation. * SW(p) shows the probability value from a Shapiro-Wilk (SW) test for normality at p=0.05. OCSB refers to the Osborn, Chui, Smith, and Birchenhall test for Seasonal Unit Roots. Here, 0 indicates there is no seasonal unit root based on the OCSB test at p=0.05. 1 indicates there is a seasonal unit root based on the OCSB test at p=0.05.

4.2 Loss Functions

We rely on the Root Mean Squared Error (RMSE), the Ratio of the RMSE (RRMSE), and the Mean Absolute Percentage Error (MAPE) as loss functions to distinguish between the accuracy of forecasts. MAPE values can be interpreted such that values less than 10% are indicative of highly accurate forecasting, 10-20% is indicative of good forecasting, and 20-50% is indicative of reasonable forecasting, whilst 50% or more indicates inaccurate forecasting (Chen et al., 2008).

As an example, we demonstrate the RRMSE calculation by providing the RMSE ratios of one form of the multivariate model (i.e., HMSSA-V) to that of ARIMA:

$$\text{RRMSE} = \frac{HMSSA-V}{ARIMA} = \frac{\left(\sum_{i=1}^{N}(\widehat{y}_{T+h,i} - y_{T+h,i})^2\right)^{1/2}}{\left(\sum_{i=1}^{N}(\widetilde{y}_{T+h,i} - y_{T+h,i})^2\right)^{1/2}},$$

where, $\widehat{y}_{T+h}$ is the h-step ahead forecast obtained by HMSSA-V, $\widetilde{y}_{T+h}$ is the h-step ahead forecast from the ARIMA model, and N is the number of the forecasts. If $\frac{HMSSA-V}{ARIMA}$ is less than 1, then forecasts from HMSSA-V outperforms ARIMA forecasts by 1-$\frac{HMSSA-V}{SNAIVE}$ percent.

5 Empirical Results

To enable replication of results we report the details of the models used to generate out-of-sample forecasts for UK tourism demand via Table 3. As the multivariate models were evaluated at different lags and the findings are reported at lag 0 and lag 12 at certain horizons, it is important to provide some additional information on how the multivariate model was set up. Figure 4 below summarises this information for the reader. Accordingly, at lag 0 the multivariate models exploit the direct relationship between the two variables (i.e., January 2004 fashion retail sales data are matched against January 2004 UK tourist arrivals data). At lag 12, the multivariate models consider fashion retail sales data from January 2004 as a predictor for UK tourist arrivals in January 2005 and so on.

Table 3: Fitted model summaries.

h	ARIMA	ETS	TBATS	NNAR	HMSSA-R	HMSSA-V
1	(0,1,1)(0,1,1)[12]	(M,Ad,M)	(0.557, 0,0, 0.959, {<12,5>})	NNAR(3,1,2)[12]	(60,22)	(60,22)
3	(0,1,1)(0,1,1)[12]	(M,Ad,M)	(0.557, 0,0, 0.959, {<12,5>})	NNAR(3,1,2)[12]	(60,22)	(60,24)
6	(0,1,1)(0,1,1)[12]	(M,Ad,M)	(0.557, 0,0, 0.959, {<12,5>})	NNAR(3,1,2)[12]	(52,12)	(60,18)
12	(0,1,1)(0,1,1)[12]	(M,Ad,M)	(0.557, 0,0, 0.959, {<12,5>})	NNAR(3,1,2)[12]	(50,12)	(51,12)

Note: For the univariate models, ETS - Exponential Smoothing, TBATS - Trigonometric Box-Cox ARMA Trend Seasonal Model, and NNAR - Neural Network Autoregression. See Hyndman and Athanasopoulos (2021) for details of the univariate model specifications noted within this table. For the HMSSA models, shown in brackets are (L,r) where L is the window length and r is the number of eigenvalues. HMSSA-R is recurrent multivariate forecast. HMSSA-V is vector multivariate forecast.

Figure 4: Inputs into the multivariate models at different lags.

The out-of-sample univariate and multivariate forecasting results for UK tourist arrivals across h=1, 3, 6 and 12 steps-ahead are reported via Table 4. Here, HMSSA-R refers to the multivariate model using a recurrent forecasting algorithm and HMSSA-V refers to the multivariate model using a vector forecasting algorithm. Initially, we evaluate the univariate forecasting outcomes. First, there was no single univariate model that can provide the best out-of-sample forecast for UK tourist arrivals across all horizons. At $h = 1$ step-ahead, the Trigonometric Box-Cox ARMA Trend Seasonal Model reports the lowest RMSE and thus the best univariate forecast. At $h = 3$ steps-ahead, ARIMA was found to be the most appropriate forecasting model based on the lowest RMSE. Interestingly, at $h = 6$ steps-ahead and $h = 12$ steps-ahead the Seasonal Naive model outperforms the competing univariate models. Therefore, if relying on univariate models alone, based on the RMSE, the use of the Trigonometric Box-Cox ARMA Trend Seasonal Model is recommended for $h = 1$ step-ahead forecasts, ARIMA for $h = 3$ steps-ahead, and Seasonal Naive for $h = 6$ and $h = 12$ steps-ahead forecasts. The MAPE values are consistent with the RMSE findings and the best univariate forecasts report MAPE values below

10%, which is indicative of highly accurate forecasting (Chen et al., 2008). Should practitioners wish to identify a single model for univariate forecasting, then based on the lowest average RMSE across all horizons, we can suggest the Seasonal Naive model as the most appropriate single univariate model for predicting UK tourism demand. However, this would not result in the most accurate forecasts at each horizon as a suite of univariate models would perform better.

Table 4: Out-of-sample forecasting Root Mean Square Error and Mean Absolute Percentage Error results for UK tourist arrivals.

	Univariate					*Multivariate*	
h	SNAIVE	ARIMA	ETS	TBATS	NNAR	HMSSA-R	HMSSA-V
1	216839	163780	167085	161389	213286	**150240**	150831
	(5.25%)	(3.98%)	(4.46%)	(4.18%)	(5.49%)	**(3.71%)**	(3.89%)
3	219235	172811	180630	177598	226087	161392	**156365**
	(5.32%)	(4.23%)	(4.69%)	(4.40%)	(5.84%)	(4.01%)	**(3.96%)**
6	222253	628109	925662	358488	266920	**[172194]**	[173591]
	(5.36%)	(16.1%)	(26.0%)	(9.45%)	(7.15%)	**([4.29%])**	([4.35%])
12	228651	466460	261429	359808	282799	[178215]	**[175844]**
	(5.58%)	(12.84%)	(6.27%)	(9.34%)	(7.08%)	([4.58%])	**([4.56%])**
Avg.	221745	357790	383702	254321	247273	165510	**164158**

Note: Shown in bold font is the model reporting the lowest RMSE and MAPE at each horizon. MAPE is shown within (). The RMSEs reported within [] indicates these results were generated by modelling the multivariate data with a 12-month lag.

Next, we focus on finding evidence for the existence of cross sector relations between tourism and fashion industries by evaluating the multivariate results in comparison to the univariate forecasting outcomes. In order to achieve this, we produce out-of-sample forecasts using the multivariate models where UK's fashion retail sales act as a leading indicator for UK tourism demand. The forecast evaluation considered different combinations at lags of 0, 3, 6, and 12 months, but we report the best outcomes only.

The results in Table 4 confirm that across all horizons, the multivariate forecasts outperform the univariate forecasts based on the RMSE and MAPE criteria. As with the univariate case, there was no single multivariate model which can outperform the competing models across all horizons. Instead, based on the RMSE and MAPE criteria, we can conclude that recurrent multivariate forecasts are best at generating out-of-sample forecasts at $h = 1$ and $h = 6$ months-ahead, whilst vector multivariate forecasts are best at $h = 3$ and $h = 12$ months-ahead.

Overall, the RMSE and MAPE criteria appear to indicate that fashion retail sales could be a leading indicator for forecasting UK tourism demand. However, this evidence was insufficient as these findings could be a result of chance occurrences. Therefore, finally, we go a step further and test the out-of-sample forecasting results for statistically significant differences using the modified Diebold-Mariano test (Harvey et al., 1997) and the two-sided Hassani-Silva test (Hassani and Silva, 2015). The findings are reported in Table 5 along with the Ratio of the Root Mean Squared Errors.

Accordingly, at $h = 1$ step-ahead, the recurrent multivariate forecast outperforms all other univariate forecasts with statistically significant results. The RRMSE indicates that recurrent multivariate forecasts are 31%, 8%, 10%, 7%, and 30% better than Seasonal Naive, ARIMA, Exponential Smoothing, TBATS, and Neural Network forecasts, respectively. However, at $h = 3$ steps-ahead, the vector multivariate forecast only produces statistically significant results in comparison to the Seasonal Naive and Neural Network forecasts whereby the vector multivariate forecast was 29% more accurate than the Seasonal Naive forecast and 31% more accurate than the Neural Network forecast. Even though the vector multivariate forecast outperforms ARIMA, Exponential Smoothing, and TBATS forecasts by 10%, 13%, and 12% respectively, there was no evidence to indicate that these are not chance occurrences. Note that the best multivariate forecasting results at $h = 1$ and $h = 3$ steps-ahead were at lag 0. However, the best multivariate forecasting results at $h = 6$ and $h = 12$ steps-ahead were found at lag 12. At $h = 6$ steps-ahead, the results are more conclusive as the recurrent multivariate model was once again seen outperforming all competing models with statistically significant outcomes. In fact, the recurrent multivariate forecasts are 23%, 73%, 81%, 52%, and 35% more accurate than the Seasonal Naive, ARIMA, Exponential Smoothing, TBATS, and Neural Network forecasts. Finally, at $h =$ 12 steps-ahead, the vector multivariate forecast was seen significantly outperforming Seasonal Naive, ARIMA, TBATS and Neural Network forecasts by 23%, 62%, 51%, and 38% respectively. However, the accuracy gains of 33% in relation to the Exponential Smoothing forecast was not statistically significant. The results in Table 5 also confirm the conclusion that as the forecasting horizon increases, the accuracy of the univariate forecasts worsen (except for the Seasonal Naive model) by a large percentage in relation to the multivariate forecasts.

Table 5 shows that there is a high number of statistically significant outcomes (i.e., 80% of the outcomes reported) and considerable forecast accuracy gains (as per the RRMSE criterion) when we consider fashion retail sales as a leading indicator for UK tourism demand. This provides sufficient evidence to conclude that UK's fashion retail sales is a statistically significant leading indicator for UK tourist arrivals.

Table 5: Out-of-sample forecasting Ratio of the Root Mean Squared Errors for UK tourist arrivals.

h	$\frac{HMSSA}{SNAIVE}$	$\frac{HMSSA}{ARIMA}$	$\frac{HMSSA}{ETS}$	$\frac{HMSSA}{TBATS}$	$\frac{HMSSA}{NNAR}$
1	$0.69^{\flat}$	0.92^{*}	0.90^{**}	0.93^{*}	$0.70^{**,\flat}$
3	$0.71^{\flat}$	0.90	0.87	0.88	$0.69^{\sharp}$
6	$0.77^{\dagger}$	$0.27^{**,\flat}$	$0.19^{**,\flat}$	$0.48^{**,\flat}$	$0.65^{*,\dagger}$
12	$0.77^{\dagger}$	$0.38^{**,\sharp}$	0.67	$0.49^{**,\flat}$	$0.62^{*,\flat}$
Avg.	0.62	0.66	0.70	0.67	0.67

Note: The RRMSE's are calculated using the multivariate model (HMSSA) which reported the lowest RMSE at each horizon (Table 4). ** indicates a statistically significant difference between the distribution of forecasts from the best HMSSA model and a competing univariate model based on the two-sided Hassani-Silva test (Hassani and Silva, 2015) at the 0.05 level and * at the 0.10 level. $^{\flat}$ indicates the existence of a statistically significant difference between the best HMSSA foreast and the competing univariate forecast based on the modified Diebold-Mariano test (Harvey et al., 1997) at the 0.01 level, $^{\sharp}$ at the 0.05 level, and † at the 0.10 level.

In summary, if practitioners are looking for the best possible forecast for UK tourism demand, based on the competing models evaluated in this study, we can suggest the following as outlined in Table 6.

Table 6: Best model for forecasting UK tourism demand at a given horizon.

	$h = 1$	$h = 3$	$h = 6$	$h = 12$
Model	HMSSA-R	HMSSA-V	HMSSA-R	HMSSA-V

Note: UK's fashion retail sales are used as a leading indicator within the HMSSA forecasting models.

It is also possible that some might prefer the use of a single model across all horizons. In such instances, based on the lowest average RMSE, we can suggest the vector multivariate model as a single model that can outperform all of the competing univariate models across all horizons.

However, it is noteworthy that we did not find any statistically significant differences between the recurrent and vector multivariate forecasts.

6 Discussion

There are several factors indicating that tourism shopping could be a major reason explaining our finding that fashion retail sales is a leading indicator for tourism demand in the UK. First, shopping is known to play an important role in tourism demand (Wu, et al., 2014; Timothy, 2005) and also known for increasing tourist arrivals (Choi et al., 2015; Choi et al., 2008). Secondly, in the context of the UK, Street (2020) reports that it is not only London that is important for tourism shopping (as argued by us in the introduction) but more than £500 million worth of tourism shopping takes place in 12,000 stores outside London annually. In fact, in 2019 tourists had spent a significant amount on shopping in other UK cities such as Edinburgh (£92 million), Manchester (£60 million), Liverpool (£32 million), and Glasgow (£23 million) too (Street, 2020). Therefore, it is likely that tourism shopping makes a significant contribution to the total retail sales volume from textile, clothing and footwear stores. Thirdly, the importance of tourism shopping for the UK was further evident during the height of the pandemic as reports indicate that British luxury brands like Burberry suffered due to weaker tourism in certain regions (Bourke, 2021). Finally, in 2013, 40.7% of UK's inbound tourists shopped for clothes or shoes (VisitBritain, 2014) and at least 57% of all visits to the UK in 2014 involved shopping (VisitBritain, 2015).

However, to explain and validate our findings further, we test UK fashion retail sales and tourism demand time series for causal effects using the Granger Causality test. This is because evidence of a causal relationship between fashion retail sales and UK tourism demand would provide more substantial evidence to support the leading indicator conclusion. The results are reported in Table 7. We found statistically significant evidence which shows that fashion retails sales have a causal effect on tourism demand in the UK. In addition, to ensure the holiday effects and weather based travel patterns are not the main cause of this causal effect, we adjust for the peaks in tourism demand and fashion retail sales and test the series again for causality. Once more, we found statistically significant evidence for a causal effect from fashion retail sales to tourism demand based on the Granger causality test.

Table 7: Granger causality test results.

Main Series (Leading Indicator)	Causality	Granger (p-value)
UK Tourist Arrivals (UK Fashion Retail Sales)	UK Fashion Retail Sales $\rightrightarrows$ UK Tourist Arrivals	$<0.01^{***}$
Adjusted for Holidays	UK Fashion Retail Sales $\rightrightarrows$ UK Tourist Arrivals	$<0.01^{***}$

Note: $\rightrightarrows$ indicates that the series on the left of the arrows causes the series on the right. *** indicates that the Granger test for causality is statistically significant at a p-value of 0.01.

For the holiday effects, instead of relying on the causality results alone, we ran the forecasting models again after removing the effect of holidays. The best outcomes are reported in Table 8. As Seasonal Naive reported the lowest average RMSE in the previous forecasting exercise, we consider this as the benchmark against our multivariate models. We found forecasts from the vector multivariate models outperforming forecasts from the Seasonal Naive models across all horizons based on the lowest RMSE. The vector multivariate forecasts are 7%, 6%, 10% and 10% more accurate than the Seasonal Naive forecasts at $h = 1$, 3, 6 and 12 months-ahead. To an extent, these results are in line with the causality findings in Table 7 as it shows forecasts from the multivariate models continuing to outperform forecasts from the Seasonal Naive model even when we removed the holiday effects. This shows that it is not the peaks (caused by holiday effects for example) that affect the multivariate modelling process but rather the dependency structure and the dynamical behaviour of the series which the multivariate models are very powerful at handling (please see, Hassani and Mahmoudvand, 2015). However, we did not find any evidence of statistically significant differences between forecasts at this stage.

Table 8: Out-of-sample forecasting RMSE and RRMSE results for UK tourist arrivals after removing the effect of holidays.

	Univariate	*Multivariate*	*RRMSE*
h	SNAIVE	HMSSA-V	$\frac{HMSSA-V}{SNAIVE}$
1	198019	**183856**	0.93
3	201850	**188946**	0.94
6	200972	**180513**	0.90
12	199828	**179894**	0.90

Note: Shown in bold font is the model reporting the lowest RMSE at each horizon.

Finally, we evidence that the gains made by the multivariate models are as a result of the proposed leading indicator and not caused by the model alone. For this purpose, we forecast UK tourism demand using univariate Singular Spectrum Analysis (Hassani et al., 2007) and compare the results against the multivariate models. The output is reported via Table 9. These results clearly show that the gains made by the multivariate models are attributable to the fashion retail sales indicator that was also found to have a causal effect on UK tourism demand as the multivariate forecasts report significantly lower RMSEs and large gains in relation to their univariate counterpart across all horizons.

Table 9: Out-of-sample forecasting RMSE and RRMSE results for UK tourist arrivals.

	Univariate		*Multivariate*		*RRMSE*	
h	SSA-R	SSA-V	HMSSA-R	HMSSA-V	$\frac{HMSSA-R}{SSA-R}$	$\frac{HMSSA-V}{SSA-V}$
1	189998	189014	**150240**	150831	$0.79^{\sharp}$	$0.80^{\dagger}$
3	199838	199077	161392	**156365**	$0.81^{\dagger}$	$0.79^{\sharp}$
6	216425	225009	[**172194**]	[173591]	$0.80^{\dagger}$	$0.77^{\sharp}$
12	244876	253984	[178215]	[**175844**]	$0.73^{\sharp}$	$0.69^{\sharp}$

Note: SSA-R refers to Recurrent Singular Spectrum Analysis forecasts. SSA-V refers to Vector Singular Spectrum Analysis forecasts. Shown in bold font is the model reporting the lowest RMSE at each horizon. The RMSEs reported within [] indicates these results were generated via modelling the multivariate data with a 12-month lag. $^{\sharp}$ indicates the existence of a statistically significant difference between the best multivariate forecast and the competing univariate forecast based on the modified Diebold-Mariano test (Harvey et al., 1997) at the 0.05 level and † at the 0.10 level.

7 Conclusion

Through our research, we make several contributions to tourism demand forecasting literature. First, we identify and present evidence for a new leading indicator (i.e., fashion retail sales) for improving the accuracy of tourism demand forecasts. In doing so, we provide empirical evidence for cross sector relations between the tourism and fashion industry from a forecasting perspective, thereby encouraging collaboration between the two industries. Second, we are the first academic study to present empirical evidence for the relationship between tourism demand and fashion retail sales from a forecasting perspective. Third, our study is the most comprehensive comparison of these multivariate models against alternatives in a tourism forecasting context as we compared the multivariate forecasts against six univariate models. Finally, we present evidence of a causal relationship between fashion retail sales and tourist arrivals in the UK.

Our findings can be of importance to the UK's government and stakeholders within the tourism and fashion industries. For example, the Office for National Statistics can benefit via the incorporation of this new leading indicator for improving tourism demand forecasts in future. The ability to generate more accurate forecasts will directly feed into more efficient resource allocations for the UK government's tourism sector deal, and also aid in better planning and decision making within the tourism industry. At a time when both the fashion industry and tourism industry in the UK are struggling, our findings show the benefits of co-operation between the two industries. For example, as fashion retail sales is a leading indicator for tourism demand, it is clear that there is scope for mutual benefit if the UK tourism industry collaborates with the UK fashion industry to include fashion in destination promotions to attract more tourists. The creation of specialist travel packages tied to fashion events, brands or iconic department stores could help the revival of both industries post-pandemic. In fact, recent research by Liberato et al. (2021) has found that fashion events not only augment the image and personality of cities but also creates a sense of loyalty whereby tourists re-visit such destinations with family and/or friends. Moreover, our findings highlight that it is important for policy makers in the UK government to call for the views of stakeholders in both fashion and tourism industries when formulating policy in future as the interlinked nature of these two industries would mean that policies should be aligned and inclusive of the needs of both industries.

However, our study is not without its limitations. First our evaluation shows the existence of a relationship pre-pandemic. As such, one might argue that these findings are irrelevant until a market correction occurs following the ongoing shock. Given that the pandemic has changed consumer behaviour, it is very likely that travel and tourism will continue to suffer longer than expected. However, interestingly, this disruption further confirms the importance of tourism shopping for the UK. For example, even though fashion brands have been trading online throughout the pandemic, they have not been able to attract the same levels of revenue that were accessible pre-pandemic. It is reasonable to assume that the lack of tourism shopping owing to the pandemic, and consumers re-evaluation of necessities would be two factors contributing to this downfall (among other factors). Second, the data limitations meant that the modelling process included all clothing, textile, and footwear retail sales from both locals and tourists. As such, it is not possible to conclude that tourism shopping is the sole reason for the relationship evidenced here. However, based on the information presented in the introduction and discussion, it is reasonable to relate this finding to tourism shopping given UK's reputation as a leading fashion destination.

Finally, our study opens several avenues for future research. First, future studies should consider evaluating how fashion retail sales impact the forecasting of tourism demand by purpose of travel. It is likely that there will be a difference in the impact of this leading indicator on leisure and business travellers to the UK. Second, it would be interesting to see how the impact of fashion retail sales vary based on a tourist's country of origin and length of stay. Third, it would be interesting to evaluate how this new leading indicator or a combination compares with the other indicators at forecasting tourism demand in the UK, enabling practitioners to group/identify the best indicators from a pool of options currently available. Fourth, future studies should compare forecasts from the multivariate models with fashion retails sales as an indicator with other multivariate models to determine which multivariate technique can exploit this relationship best. Fifth, it would be interesting to collaborate with the Office for National Statistics and obtain data that differentiates between online and offline fashion sales as its possible that tourists would prefer to shop offline rather than online when visiting a destination. Finally, it would be interesting to evaluate this relationship in other tourism markets where fashion is identified as a key economic driver to determine whether this relationship holds. Whilst our research has evidenced (at a macro-level, due to data availability constraints) the existence of a useful relationship between fashion retail sales and tourism demand from a forecasting context, engagement with the suggestions for future research would enable a more in-depth and focused analysis of the impact of fashion retail sales on forecasting tourism demand.

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