Cross Country Relations in European Tourist Arrivals*

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Abstract

This paper introduces an optimized Multivariate Singular Spectrum Analysis (MSSA) algorithm for identifying leading indicators. Exploiting European tourist arrivals data, we analyse cross country relations for European tourism demand. Cross country relations have the potential to aid in planning and resource allocations for future tourism demand by taking into consideration the variation in tourist arrivals across other countries in Europe. Our findings indicate with statistically significant evidence that there exists cross country relations between European tourist arrivals which can help in improving the predictive accuracy of tourism demand. We also find that MSSA has the capability of not only identifying leading indicators, but also forecasting tourism demand with far better accuracy in comparison to its univariate counterpart, Singular Spectrum Analysis.

Keywords: Multivariate Singular Spectrum Analysis; leading indicators; tourist arrivals; demand; Europe.

1 Introduction

Europe is considered as the world's most visited tourism destination (UNWTO, 2016) with five European Union (EU) member states and one of its candidate countries being listed among the world's top 10 destinations for holiday makers (European Commission, 2016). In 2015, whilst generating an income of US$ 451 billion, the EU accounted for 51% of the global tourist arrivals which in absolute terms was a 27 million increase in relation to 2014 (UNWTO, 2016). As the EU has placed considerable emphasis on the tourism sector as a source of economic prosperity for its members countries (Lee and Brahmasrene, 2013), and given that Europe has suffered dramatically from the global financial crisis and the ongoing European debt crisis, the need for accurate forecasts of tourism demand is of paramount importance for tourism planning, entrepreneurs, investors, policy makers, tour operators and others alike.

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There exists numerous studies which consider both univariate and multivariate forecasting applications of tourist arrivals. However, the aim of this paper goes beyond obtaining a forecast alone. In particular, our interest lies in answering the question as to whether one country's tourist arrivals can act as an indicator for the behaviour of tourism demand in another. The use of leading indicators for forecasting tourist arrivals is popular (Zhang and Kulendran, 2016), and the use of indicators for improving tourism demand forecasts have been discussed over many years. Yet, most of the focus has been on determining whether macroeconomic variables function as drivers of tourism demand, see for example Seetaram et al. (2016), Eugenio-Martin and Campos-Soria (2014), and Smeral (2012). Recently, there has been interest in exploring factors beyond the macroeconomic sphere (Dragouni et al., 2016) and our work intends on contributing further to this line of research.

In order to achieve the aim of this paper, we consider modelling and finding cross country relations for selected European tourist arrivals in Austria, Cyprus, Germany, Greece, Netherlands, Portugal, Spain, Italy, Sweden and the United Kingdom. The choice of countries is mainly based on data availability. However, a closer look at these countries indicate the continuing and growing importance of tourism within each destination, and thereby justifies the selections. For example, Spain, Italy, Germany and UK are ranked amongst the top 10 destinations for international tourist arrivals (UNWTO, 2016). In addition, destinations such as Portugal, Greece and Cyprus are recognized as established destinations based on increasing tourist arrivals in 2015, whilst the Netherlands and Austria too have recorded solid increases, with Sweden boasting double digit growth (UNWTO, 2016). Table 1 below highlights some key statistics relating tourism to economic growth, employment and degree of seasonality in the selected countries.

Table 1: Total contribution of travel and tourism to GDP and Employment in 2014, and seasonality in tourist arrivals.

	GDP	Employment	R^2
Germany	8.9%	11.7%	0.921
Greece	17.3%	19.4%	0.875
Spain	15.2%	15.3%	0.961
Italy	10.1%	11.4%	0.904
Cyprus	21.3%	7.7%	0.915
Netherlands	5.6%	9.8%	0.830
Austria	13.5%	14.5%	0.917
Portugal	6%	18.4%	0.928
Sweden	9.5%	11%	0.949
United Kingdom	10.5%	12.7%	0.810

Note: The data have been compiled via various Travel & Tourism Economic Impact 2015 reports published by the World Travel & Tourism Council (https://www.wttc.org/). Percentages reported under GDP should be interpreted in relation to total GDP in the respective country. Percentages reported under employment should be interpreted in relation to total employment in the respective country. R^2 denotes the seasonal R-square which measures the dominance of seasonality within each series.

The main advantage in identifying a cross country indicator for tourist arrivals is that it enables one to study the tourism policy decisions and investments in a neighbouring country, and alter its current policies and investments in the tourism sector accordingly. Moreover, the identification of such indicators has the potential to help improve forecast accuracy. As such, there is scope to benefit from efficient and improved decision making, planning and resource allocations particularly in relation to staffing and crucial investments in accommodation, aircrafts and infrastructure.

Historically, econometric models have been the most widely used for forecasting tourist arrivals (Rosselló, 2001). However, in this paper we consider a nonparametric, time series analysis technique known as Multivariate Singular Spectrum Analysis (MSSA) for modelling and finding leading cross country indicators for European tourism demand. We use the univariate counterpart of MSSA, Singular Spectrum Analysis (SSA) as the benchmark model, instead of relying on other popular univariate models such as ARIMA, ETS and Neural Networks because in Hassani et al. (2015) it was shown via an application into U.S. tourism demand forecasting that SSA has the capability of outperforming these methods. More recently, Hassani et al. (2017) evaluated the use of several parametric and nonparametric univariate forecasting techniques for predicting tourism demand in the same European countries and found SSA outperforming the competing models. In addition, the use of basic univariate SSA as a benchmark provides a further advantage as it enables to clearly show the accuracy gains attainable via the MSSA approach proposed in this paper.

Figure 1 below plots the time series for European tourist arrivals. As Chen et al. (2008) note, if stationary, a series will have a constant sample mean, variance and autocorrelation function over time. However, the series in Figure 1 clearly shows both growth and declines which are signs of structural breaks in some series, and such breaks are infamous for making a time series non-stationary (Hassani et al., 2014). The nature of these time series indicate that forecasting techniques which are model free, and thus not bound by the restrictive parametric assumptions of normality and stationarity could provide comparatively better modelling for such data. In addition, the importance of filtering capabilities within such time series methods are apparent as there is a potential to benefit from extracting the seasonal fluctuations which are clearly visible. The proposed MSSA model is not only nonparametric and therefore not bound by the parametric assumptions, but is also a popular filtering and signal extraction technique.

As can be seen from Figure 1, the movements of all the tourist arrivals series are dominated by seasonality. These strong seasonal patterns are underlined by the seasonal R^2 presented in the last column of Table 1. This is computed as the conventional coefficient of determination in a regression model of the first difference series against twelve monthly dummy variables. Monthly dummy variables account for over 90% of the variation in most of these series, with the smallest seasonality reported for the UK as 81%. The similar characteristics of tourist arrivals in these countries is mainly because all the countries selected are in Europe and geographically close to each other, have similar climate conditions and macro-economic factors. In fact, tourists may visit several European countries in one occasion and thus visiting one country may well contribute to tourism revenues of other selected countries with freedom of movement facilitating tourist travelling, except the UK which is an island and has tighter boarder controls. Therefore, we would expect that the multivariate framework (MSSA) would produce better and more accurate forecasts, taking advantage of the similar behaviour of these series.

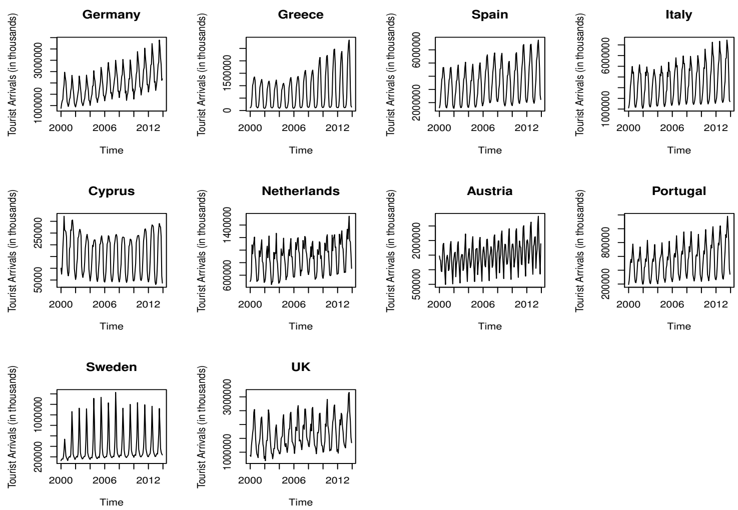

Figure 1: Tourist arrivals over time (Jan. 2000 - Dec. 2012).

It is noteworthy that the aim of this study and its findings can be of great importance to the EU tourism sector as the recovery of many European economies in the year 2015 has fuelled intra-regional tourism (UNWTO, 2016). As a research study focussed on identifying leading cross country relations for European tourist arrivals, this paper has several key contributions. Firstly, it marks the introduction of MSSA for tourism demand modelling and forecasting. The use of an optimized MSSA algorithm as a method of seeking out indicators across countries is novel. This algorithm is extremely useful as it is coded in R to enable users who are not conversant with the theory underlying MSSA to use this method for selecting the optimized MSSA parameters for obtaining the best possible MSSA forecast. The accuracy of forecasts, efficiency, and ease of use are all important attributes when choosing a forecasting technique, and time series methods often yield more accurate forecasting results than causal quantitative approaches (Chen et al., 2008). Thirdly, as noted in Yap and Allen (2011), majority of the tourism demand research focuses on income and price variables as demand determinants for travel. In contrast to historical studies, this application considers uncovering cross country relations in tourist arrivals, and introduces a methodology which can be applied universally for seeking out leading indicators in any format for the entire tourism sector. Finally, the study considers short, medium and long run forecasts when determining the leading cross country relations in European tourist arrivals.

The remainder of the paper is organised as follows. Section 2 presents a concise literature review. Section 3 briefly discusses the univariate SSA process and then introduces the optimized MSSA algorithm for leading indicators. Section 4 analyses the data used and presents the measures employed for evaluating forecast accuracy. Section 5 presents the empirical results and the paper concludes in Section 7.

2 Literature Review

This section focuses on research exploiting indicators for the benefit of the tourism industry, and for improving tourism demand forecasting.

Turner et al. (1997) uses cross-correlation techniques for finding indicators for tourist arrivals to Australia from U.S., Japan, UK and New Zealand. They consider a variety of national indicators which include income, unemployment, forward exchange rate, money supply, price ratio, industrial production, imports and exports. In addition to analysing based on the total tourist arrivals, the forecasting exercise also considers further disaggregated data based on travel type such that 'holiday', 'visiting friends and relatives' (VFR) and 'business' are considered. The findings of this study remain inconclusive in terms of whether leading indicator models can provide more accurate forecasts than univariate ARIMA models. McCool et al. (2001) considers the tourism industry in the state of Montana, U.S. alongside a qualitative research approach aimed at identifying the usefulness of 26 indicators of sustainability (as identified in Manning (1992)) for the states' tourism industry. The results from the study left more questions than answers as there were differences between what should be sustained and appropriate indicators.

Cho (2001) uses exponential smoothing (ETS), ARIMA and an adjusted ARIMA model for predicting tourist arrivals from different countries to Hong Kong. He finds the adjusted ARIMA model (which considers economic variables as indicators), outperforms ARIMA and ETS forecasts for tourist arrivals from Japan whilst ARIMA is found to be the best predictor for tourist arrivals from U.S. and UK. There is no difference between forecasts from ARIMA and adjusted ARIMA in the case of Taiwan, Singapore and Korea with ETS found to be the least effective method. Rosselló (2001) uses leading indicators to predict turning points in tourist arrivals into Balearic Islands from UK and Germany. The author uses cross-correlation techniques for identifying indicators which relate to economic activity, prices and financial activity, and classifies these as leading, coincident or lagged. Following a comparison of the performance of forecasts from ARIMA, naive and leading indicator methodologies (using regression), the author finds that turning points are best predicted by the leading indicator methodology.

Leading indicator Transfer Function (TF) models are developed to forecast tourism demand from UK to six major destinations by Kulendran and Witt (2003). The performance of the TF forecasts are compared with ARIMA and Error Correction Model (ECM) forecasts. The authors find that the TF and ARIMA based models outperform ECM in the short run whilst ECM provides better forecasts in the long run. However, their findings also suggest that leading indicator models cannot outperform univariate ARIMA forecasts, and thereby concludes that practitioners should not consider complex leading indicator models. Qualitative research has also been adopted in the search for indicators in the tourism industry. For example, Fucsh and Weiermair (2004) looks at the possibility of exploiting indicator systems for exploring guest satisfaction whilst Phillips and Louvieris (2005) identifies indicators which are used to develop a balanced scorecard for the hotel sector, and de Sausmarez (2007) studies the role of indicators for sustainable tourism development and concludes that the travel trade may hold the key to indicators of market trends.

Becken (2008) applies 10 indicators of oil intensity to compare the Top 10 tourist markets to New Zealand. She finds considerable differences in oil use between the top 10 markets to New Zealand arising through differences in the lengths of stay, travel itineraries and transport modes. Kulendran and Wong (2009) exploits a single input leading indicator model for predicting numerical demand growth rates, directional changes and turning points in the growth rate for Hong Kong. An ARIMA model and a no-change model is used for comparative purposes and the authors find that ARIMA forecasts outperform the other two models in terms of the numerical forecasting exercise. However, the single input leading indicator model outperformed ARIMA and the no-change models in the turning point and directional change forecasting comparisons. Meanwhile, Yap and Allen (2011) uses a panel three-stage least squares (3SLS) model to investigate the role of leading indicators such as consumers perceptions of the future course of the economy, household debt and the number of hours worked in paid jobs on Australian domestic tourism demand.

Lozano and Gutierrez (2011) and Marcussen (2011) applied Multidimensional Scaling (MDS) to summarize indicators further within the tourism industry. A Threshold Autoregression (TAR) model was exploited in Che (2013) to determine whether the destination's consumer price index (CPI) influenced outbound tourism in Taiwan and the author found evidence of a positive linear relationship. Kosnan et al. (2013) exploits the Gravity model along with panel data to identify the determinants of international tourism in Malaysia. Yap and Saha (2013) uses fixed-effects panel data analysis for 139 countries and finds that political instability, heritage and terrorism can be indicators which have a negative influence on tourism demand.

Guizzardi and Stacchini (2015) exploit business sentiment surveys as indicators in naive and structural time series models for real-time forecasting of regional tourism and finds it aiding in the improvement of goodness of fit and forecasting performance. Gunter and Onder (2015) performs a comparative study at forecasting international city tourism demand for Paris using a variety of techniques which includes the Error Correction - Autoregressive Distributed Lag Model (EC-ARDL), classical and Bayesian VAR, Time-varying Parameter (TVP), ARMA, ETS and the naive-1 model. Within this study, the authors seek to determine whether multivariate models with city destination's own price, prices of competing European destinations, and tourist income have any predictive power. They find that not one single model can outperform all others on all occasions. The possibility of exploiting Google and Baidu search engine data for improving tourism demand forecasts in China was evaluated by Yang et al. (2015) with the use of ARMA models. They found Baidu data to be a comparatively better indicator than Google data for the Chinese market. Artola et al. (2015) seeks to determine whether internet searches can help predict tourism inflows into Spain by considering an ARIMA model estimated by Time Series Regression with ARIMA Noise, Missing Observations, and Outliers, and another model augmented with the Google-index. Likewise, Bangwayo-Skeete and Skeete (2015) also evaluated whether Google data can be an indicator for tourism demand forecasting. They considered Autoregressive Mixed-Data Sampling models and compared the results with Seasonal ARIMA (SARIMA) and Autoregressive (AR) models to find that Google trends does in fact help predict tourism demand.

Tica and Kozic (2015) use the Granger causality test to identify leading indicators for forecasting Croatian inbound tourism demand. They find real GDP, imports in Poland, and gross wages in the Czech Republic and Slovakia to be the most important leading indicators. Mehmood et al. (2016) evaluates the relationship between tourist arrivals, immigrants and crimes in US via Ordinary Least Squares (OLS) and ARDL methods. They find that crime rates have a negative and significant effect on tourist arrivals. Principal Component Analysis was used by Claveria (2016) to find interactions between tourism and economic variables in 20 emerging markets. The Gravity model was used more recently by Wang and Xi (2016) who found cultural dummy variables and climate variables driving tourism flows to China. Chatziantoniou et al. (2016) considers a variety of SARIMA models to determine which macroeconomic variables can act as indicators for improving tourism forecasts. Zhang and Kulendran (2016) seek to quantify the link between climate variables and inbound tourism demand in Hong Kong using the Euclidean distance statistics and finds climate variables having a significant impact on shaping seasonal variation.

Support Vector Regressions were used in Jackman and Naitram (2016) to determine if Google search data can act as an indicator for trends in tourist arrivals in Barbados. The authors find that whilst Google Trends data can pick up significant information pertaining to tourist arrivals from UK and Canada there is no evidence in terms of tourist arrivals from US. Habibi (2016) uses generalized method of moment model to identify determinants of inbound tourism to Malaysia. Pintassilgo et al. (2016) combined a world gravity model of tourism flows with an input-output model to identify if climate variables act as indicators for tourism flow in Portugal.

Based on the tourism demand literature, it is evident that a wide variety, and mostly parametric techniques have been adopted in the search for leading indicators for tourism demand, and that most of the models used have been unable to outperform ARIMA. In addition, historically linear models have been used for identifying indicators for tourism demand. However, such models fail to capture the nonlinear relationships in data. Accordingly, proposed in this paper is the use of a Multivariate SSA based approach for finding leading indicators for tourism demand and using these indicators for obtaining more accurate forecasts. Whilst this paper marks the introductory application of MSSA in the tourism sector, its univariate counterpart, SSA has been applied successfully on two previous occasions. Beneki et al. (2009) introduced SSA as a feasible option for forecasting tourism income and showed that SSA outperforms Seasonal ARIMA (SARIMA) and time-varying-parameter state space models. Thereafter, Hassani et al. (2015) introduced SSA for tourism demand forecasting and showed that SSA can outperform an optimized ARIMA model, Neural Networks and ETS via an application to aggregated and disaggregated forecasts of U.S. tourist arrivals.

3 Methodology

3.1 Singular Spectrum Analysis

Univariate SSA

SSA initially decomposes the original data into trend, periodic and noise components. In the second stage, the original time series is reconstructed following noise reduction and forecasts are obtained via a linear recurrence formula. A detailed description of the two main stages of SSA (i.e. Decomposition and Reconstruction) can be found in Sanei and Hassani (2015). Here, the univariate SSA process is concisely summarized in Figure 2 and an explanation of the forecasting algorithms follow.

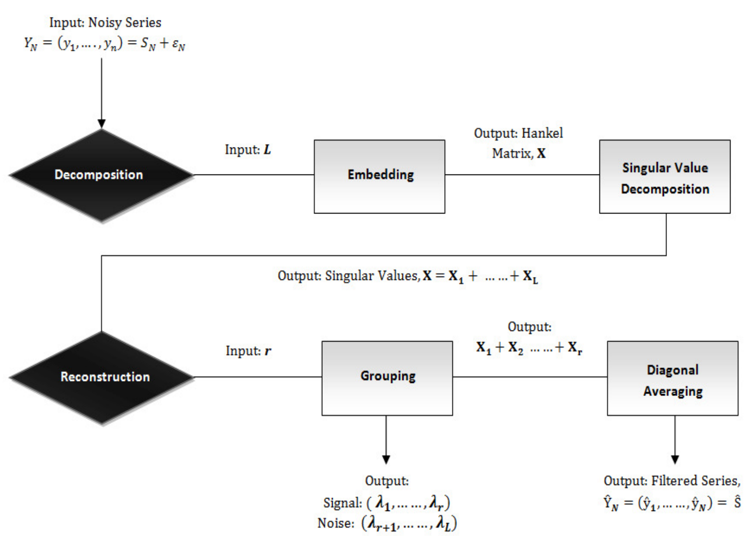

Figure 2: A summary of the basic SSA process.

SSA-R

When using SSA, one can generate forecasts via the recurrent (SSA-R) or vector (SSA-V) forecasting methods. The SSA-R process considers only the last component of the reconstructed vectors for forecasting whilst the SSA-V process takes into consideration the information contained within the entire vector. Previous research suggests the SSA-V forecasting approach is less sensitive to structural breaks in series and can provide better forecasts than SSA-R under such circumstances (Hassani et al., 2015). However, this study considers both vector and recurrent forecasting approaches and compare between the results. A detailed description of the SSA-R forecasting approach can be found in Sanei and Hassani (2015). It is summarised below.

Let $v^2 = \pi_1^2 + \ldots + \pi_r^2$, where π_i is the last component of the eigenvector U_i $(i = 1, \ldots, r)$. Moreover, suppose for any vector $U \in \mathbf{R}^L$ denoted by $U^\triangledown \in \mathbf{R}^{L-1}$ the vector consisting of the first $L-1$ components of the vector U. Let $y_{N+1}, \ldots, y_{N+h}$ show the h terms of the SSA recurrent forecast. Then, the h-step ahead forecasting procedure can be obtained by the following formula

$$y_i = \begin{cases} \widetilde{y}_i & \text{for } i = 1, \ldots, N \\ \sum_{j=1}^{L-1} \alpha_j y_{i-j} & \text{for } i = N+1, \ldots, N+h \end{cases} \tag{1}$$

where $\widetilde{y}_i$ $(i = 1, \ldots, N)$ creates the reconstructed series (noise reduced series) and vector $A = (\alpha_{L-1}, \ldots, \alpha_1)$ is computed by:

$$A = \frac{1}{1 - v^2} \sum_{i=1}^{r} \pi_i U_i^\triangledown. \tag{2}$$

SSA-V

Consider the following matrix

$$\Pi = \mathbf{V}^\triangledown (\mathbf{V}^\triangledown)^T + (1 - v^2) A A^T \tag{3}$$

where $\mathbf{V}^\triangledown = [U_1^\triangledown, ..., U_r^\triangledown]$. Now consider the linear operator

$$\theta^{(v)} : \mathfrak{L}_r \mapsto \mathbf{R}^L \tag{4}$$

where

$$\theta^{(v)} U = \begin{pmatrix} \Pi U^\triangledown \\ A^T U^\triangledown \end{pmatrix}. \tag{5}$$

Define vector Z_i as follows:

$$Z_i = \begin{cases} \widetilde{X}_i & \text{for } i = 1, \ldots, K \\ \theta^{(v)} Z_{i-1} & \text{for } i = K+1, \ldots, K+h+L-1 \end{cases} \tag{6}$$

where, $\widetilde{X}_i$'s are the reconstructed columns of the trajectory matrix after grouping and eliminating noise components. Now, by constructing matrix $\mathbf{Z} = [Z_1, ..., Z_{K+h+L-1}]$ and performing diagonal averaging we obtain a new series $y_1, ..., y_{N+h+L-1}$, where $y_{N+1}, ..., y_{N+h}$ form the h terms of the SSA vector forecast.

3.2 Automated Horizontal Multivariate SSA (HMSSA) Algorithm for Leading Indicators of Tourism Demand

We use an automated and optimized MSSA algorithm in this paper to find leading cross country indicators for tourism demand [1]. In brief, the algorithm is designed to evaluate two given time series and determine the selection of SSA choices which can provide the best forecast by minimizing a loss function. Therefore, we evaluate every possible combination of cross country relations for tourism demand in Europe and select as leading indicators the countries which when combined together can provide the most accurate forecast by producing a comparatively lower forecast error. A detailed explanation of the theory underlying MSSA is presented in Sanei and Hassani (2015). Presented herewith are the Automated Horizontal MSSA algorithm used in our work and we mainly follow the notations in Sanei and Hassani (2015).

HMSSA-R Optimal Forecasting Algorithm

1. Consider M (in this case two) time series with identical series lengths of N_i, such that $Y_{N_i}^{(i)} = (y_1^{(i)}, \ldots, y_{N_i}^{(i)})$ $(i = 1, \ldots, M)$. M is assumed to be noisy time series.

2. Divide both series into two parts leaving $\frac{2}{3}^{rd}$ for model training and testing, and $\frac{1}{3}^{rd}$ for validation.

3. Begin with a fixed value for the Window Length L, such that $L = 2$ $(2 \leq L \leq \frac{N}{2})$ and in the process, evaluate all possible values of L for Y_{N_i}, use the training data to construct the trajectory matrix $\mathbf{X}^{(i)} = [X_1^{(i)}, \ldots, X_K^{(i)}] = (x_{mn})_{m,n=1}^{L,K_i}$ for each single series $Y_{N_i}^{(i)}$ $(i = 1, \ldots, M)$ separately. These trajectory matrices are LxK Hankel matrices where $K_i = N_i - L_i + 1$.

4. Thereafter, we must obtain the block Hankel matrix in the horizontal form. For this, we need to have $L_1 = L_2 = ... = L_M = L$. Therefore, we have different values of K_i and series length N_i, but similar L_i. The block trajectory matrix $\mathbf{X}_H$ appears as:

$$\mathbf{X}_H = \left[\begin{array}{cccc} \mathbf{X}^{(1)} : & \mathbf{X}^{(2)} : & \cdots & : \mathbf{X}^{(M)} \end{array} \right].$$

5. Let $U_{H_j} = (u_{1j}, \ldots, u_{Lj})^T$, with length L, be the jth eigenvector of $\mathbf{X}_H \mathbf{X}_H^T$ which represents the Singular Value Decomposition. The SVD is obtained by $\mathbf{X}_H \mathbf{X}_H^T$ which results in a matrix that does not have any cross-product between Hankel matrices $\mathbf{X}^{(i)}$ and $\mathbf{X}^{(j)}$. Moreover, the sum of $\mathbf{X}^{(i)} \mathbf{X}^{(i)^T}$ produces the new block Hankel matrix.

6. Evaluate all possible combinations of the number of eigenvalues, r $(1 \leq r \leq L-1)$ step by step for the selected L and construct $\widehat{\mathbf{X}}_H = \sum_{i=1}^{r} U_{H_i} U_{H_i}^T \mathbf{X}_H$ as the reconstructed matrix obtained using r eigentriples:

$$\mathbf{X}_H = \left[\begin{array}{cccc} \widehat{\mathbf{X}}^{(1)} : & \widehat{\mathbf{X}}^{(2)} : & \cdots & : \widehat{\mathbf{X}}^{(M)} \end{array} \right].$$

7. Consider matrix $\widetilde{\mathbf{X}}^{(i)} = \mathcal{H} \widehat{\mathbf{X}}^{(i)}$ $(i = 1, \ldots, M)$ as the result of the Hankelization procedure of the matrix $\widehat{\mathbf{X}}^{(i)}$ obtained from the previous step for each possible combination of SSA choices.

[1] The R-codes for the automated MSSA algorithms are available upon request.

8. Let $U_{H_j}^{\triangledown}$ denote the vector of the first $L-1$ coordinates of the eigenvectors U_{H_j}, and π_{H_j} indicate the last coordinate of the eigenvectors U_{H_j} $(j = 1, \dots, r)$.

9. Define $\upsilon^2 = \sum_{j=1}^{r} \pi_{H_j}^2$.

10. Denote the linear coefficients vector $\mathcal{R}$ as follows:

$$\mathcal{R} = \frac{1}{1-\upsilon^2} \sum_{j=1}^{r} \pi_{Hj} U_{Hj}^{\triangledown}. \tag{7}$$

11. If $\upsilon^2 < 1$, then the h-step ahead HMSSA forecasts exist and is calculated via the formula:

$$\left[\hat{y}_{j_1}^{(1)}, \dots, \hat{y}_{j_M}^{(M)}\right]^T = \begin{cases} \left[\tilde{y}_{j_1}^{(1)}, \dots, \tilde{y}_{j_M}^{(M)}\right], & j_i = 1, \dots, N_i, \\ \\ \mathcal{R}^T \mathbf{Z}_h, & j_i = N_i + 1, \dots, N_i + h, \end{cases} \tag{8}$$

where, $\mathbf{Z}_h = \left[Z_h^{(1)}, \dots, Z_h^{(M)}\right]^T$ and $Z_h^{(i)} = \left[\hat{y}_{N_i-L+h+1}^{(i)}, \dots, \hat{y}_{N_i+h-1}^{(i)}\right]$ $(i = 1, \dots, M)$.

12. Find the combination of L and r which minimises a loss function, $\mathcal{L}$ and thus represents the optimal HMSSA-R choices for decomposing and reconstructing in a multivariate framework.

13. Finally use the selected optimal L to decompose the series comprising of the validation set, and then select r singular values for reconstructing the less noisy time series, and use this newly reconstructed series for forecasting the remaining $\frac{1}{3}^{rd}$ observations.

HMSSA-V Optimal Forecasting Algorithm

1. Follow steps in 1-9 of the HMSSA-R optimal forecasting algorithm above.

2. Then, consider the following matrix

$$\mathbf{\Pi} = \mathbf{U}^{\triangledown} \mathbf{U}^{\triangledown T} + (1-\upsilon^2) R R^T, \tag{9}$$

where $\mathbf{U}^{\triangledown} = [U_1^{\triangledown}, ..., U_r^{\triangledown}]$. Now use the linear operator

$$\mathcal{P}^{(v)} : \mathfrak{L}_r \mapsto \mathbb{R}^L, \tag{10}$$

where

$$\mathcal{P}^{(v)} Y = \begin{pmatrix} \mathbf{\Pi} Y_{\triangle} \\ R^T Y_{\triangle} \end{pmatrix}, \ Y \in \mathfrak{L}_r, \tag{11}$$

and $Y_{\triangle}$ is vector of last $L-1$ elements of Y.

3. Define vector $Z_j^{(i)}$ $(i = 1, \dots, M)$ as follows:

$$Z_j^{(i)} = \begin{cases} \widetilde{X}_j^{(i)} & \text{for } j = 1, \dots, k_i \\ \mathcal{P}^{(v)} Z_{j-1}^{(i)} & \text{for } j = k_i + 1, \dots, k_i + h + L - 1 \end{cases} \tag{12}$$

where, $\widetilde{X}_j^{(i)}$'s are the reconstructed columns of trajectory matrix of the i^{th} series after grouping and leaving noise components.

4. Thereafter, by constructing matrix $\mathbf{Z}^{(i)} = [Z_1^{(i)}, ..., Z_{k_i+h+L-1}^{(i)}]$ and performing diagonal averaging we obtain a new series $\hat{y}_1^{(i)}, ..., \hat{y}_{N_i+h+L-1}^{(i)}$, where $\hat{y}_{N_i+1}^{(i)}, ..., \hat{y}_{N_i+h}^{(i)}$ provides the h step ahead HMSSA-V forecast for the selected combination of L and r.

5. Finally, follow steps 12-13 in the HMSSA-R optimal forecasting algorithm to find the optimal L and r for obtaining HMSSA-V forecasts.

Below, we briefly comment upon the benefits, differences and similarities between SSA/MSSA and other time series analysis and forecasting techniques such as ARIMA, Exponential Smoothing (ETS) and Neural Networks (NN). Firstly, ARIMA, ETS and NN are classical time series methods which forecast both signal and noise. The moving average component of ARIMA is known to provide better forecasts when presented with less volatile data whilst basic versions of ETS such as single exponential smoothing cannot be used in the presence of seasonality (Chen et al., 2008). In comparison, SSA/MSSA filters the noise in time series and generates forecasts using a newly reconstructed less noisy time series. Secondly, SSA and MSSA techniques enable users to extract signals in time series and forecast these signals separately, a distinguishing characteristic in relation to the classical time series models. There are several recent and diverse applications which have benefited from these qualities. See for example, *inter-alia* Huang et al. (2017), Ghodsi (2015), Ghodsi et al. (2015), Ghodsi and Omer (2014) and Cassiano et al. (2013). MSSA in particular offers the ability of modelling time series with different series lengths, see for example Hassani and Silva (2016). Thirdly, SSA/MSSA are not bound by the parametric restrictions of stationarity whereas ARIMA and ETS methods require that the time series are stationary for forecasting to make sense (Chen et al., 2008). Fourthly, methods such as ARIMA require longer historical data sets to produce a reliable forecast (Chen et al., 2008). However, SSA/MSSA can produce a forecast with a minimum of 3 observations and readers are referred to Silva and Hassani (2015) where they can see the results from an application with few observations. Finally, SSA and ARIMA models share some similarities as reported in Hassani and Thomakos (2010) and Silva and Hassani (2015) according to whom, if we denote β as a fixed $(L \times 1)$ vector, then when $\beta = [-1, 1]$ and $L = 2$ we have the first differences of the realization as $\beta\mathbf{X}$. Furthermore, setting $L \geq 2$ and $\beta = [1/L, 1/L, \ldots, L]$ gives us a L-order moving average for the realization as $\beta\mathbf{X}$. Moreover, the linear recurrent formula which is used for forecasting in SSA is

$$y_{i+d} = \sum_{k=1}^{d} \alpha_k y_{i+d-k}, \tag{13}$$

where $1 \leq i \leq N - d$, is closely identical in structure to autoregressive models even though the calculation of the parameters differ.

4 The Data and Metrics

4.1 The Data

The data used in this study which relates to monthly international tourist arrivals into 10 European nations was extracted via the Eurostat database (http://ec.europa.eu/eurostat/data/database, the data and forecasts are available upon request). The use of monthly data is important as previous research exploiting monthly data in tourism is limited, with less than 10% of tourism demand forecast articles using data with a monthly frequency (Gunter and Onder, 2015; Song et al. (2009). Table 2 reports some key descriptive statistics for tourist arrivals including results from the tests for normality and seasonal unit roots. During the 13 year period, the highest median tourist arrivals was reported in Italy whilst the lowest median tourist arrivals had been in Cyprus. Based on the standard deviation, the most variation in tourist arrivals was recorded in Italy whilst the least variation was in Cyprus. The normality test indicates that majority of the tourist arrivals series are skewed whilst the OCSB (Osborn et al. 1988) test for seasonal unit roots indicates that except for the series pertaining to tourist arrivals in the Netherlands, all other series have seasonal unit roots.

Table 2: Descriptive statistics for tourist arrivals (Jan. 2000 - Dec. 2013).

	Mean	Med.	SD	SW (p)	OCSB
Germany	1953000	1849000	641550	<0.01	1
Greece	762900	555100	686634	<0.01	1
Spain	3449000	3429000	1366387	<0.01	1
Italy	3415000	3442000	1653644	<0.01	1
Cyprus	158692	187800	83409	<0.01	1
Netherlands	874767	895900	241150	<0.01	0
Austria	1501201	1480754	475432	0.67*	1
Portugal	533720	531457	227719	<0.01	1
Sweden	383473	240430	303655	<0.01	1
United Kingdom	1628266	1495147	546790	<0.01	1

Note: * indicates data is normally distributed based on a Shapiro-Wilk (SW) test at p=0.05. 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.

Next, we test the tourist arrivals series for break points using the Bai and Perron (2003) test and the output is reported in Table 3. As 2011 April is the last structural break experienced by at-least one of the countries, we use data from January 2000 - April 2011 for training and testing the forecasting models, and set aside as validation sets the observations from May 2011 - December 2013 which is approximately 2.5 years. This separation allows us to determine the impact of structural breaks on the training process of both SSA and MSSA.

Table 3: Structural breaks in the tourist arrivals series.

Series	Structural Break
Germany	2005(4), 2011(4)
Greece	2009(4)
Spain	2006(3)
Italy	2010(4)
Cyprus	None
Netherlands	2011(3)
Austria	2007(5)
Portugal	2006(3)
Sweden	None
United Kingdom	2005(4)

Also, as SSA is a filtering technique, we find it pertinent to present some additional information on the separation of signal and noise via SSA. We call upon the weighted correlation (w-correlation) statistic for this purpose. The w-correlation shows the dependence between two time series and it can be calculated as (Sanei and Hassani, 2015):

$$\rho_{12}^{(w)} = \frac{\left(Y_N^{(1)}, Y_N^{(2)}\right)_w}{\| Y_N^{(1)} \|_w \| Y_N^{(2)} \|_w},$$

where $Y_N^{(1)}$ and $Y_N^{(2)}$ are two time series, $\| Y_N^{(i)} \|_w = \sqrt{\left(Y_N^{(i)}, Y_N^{(i)}\right)_w}$, $\left(Y_N^{(i)}, Y_N^{(j)}\right)_w = \sum_{k=1}^{N} w_k y_k^{(i)} y_k^{(j)}$ $(i, j = 1, 2)$, w_k=min$\{k, L, N-k\}$ (here, assume $L \leq N/2$).

The SSA decomposition of the series provides more accurate results, if the resulting additive components of the series are approximately separable from each other. If the value of the w-correlations is small, then the corresponding series is almost w-orthogonal, but, if it is large, then the two series are far from being w-orthogonal (Hassani et al. 2013c). Accordingly, if the w-correlation value between two reconstructed components are close to 0, then it confirms that the corresponding time series are w-orthogonal and are well separable (Hassani et al. 2009). Table 4 shows the w-correlations for all SSA decompositions by comparing the two components of signal and noise. Here, we use as signal the reconstructed series containing r components and select the remaining r (which does not belong to the reconstruction) as noise. It is clear that all w-correlations are close to 0 and this confirms that SSA has successfully achieved a sound separation between noise and signal during the decomposition process.

Table 4: W-correlations between signal and residuals for tourist arrivals.

Series	SSA-V	SSA-R
Germany	0.005	0.005
Greece	0.006	0.006
Spain	0.005	0.005
Italy	0.004	0.004
Cyprus	0.010	0.010
Netherlands	0.009	0.009
Austria	0.005	0.006
Portugal	0.006	0.006
Sweden	0.020	0.020
United Kingdom	0.014	0.014

4.2 Metrics

Root Mean Squared Error (RMSE)

This study relies mainly on two main metrics for measuring and distinguishing between the accuracy of forecasts[2]. The first is the Root Mean Squared Error (RMSE) criterion which is widely adopted in forecasting literature, see for example, Hassani et al. (2009;2013b;2015). Here, in order to save space, we only provide the RMSE ratios of SSA-R to that of SSA-V:

[2]In addition to the RMSE and RRMSE criteria we have also reported the results from Mean Absolute Error (MAE) and Mean Absolute Percentage Error (MAPE) via Table 8 in the Appendix for those who prefer these criteria. According to Chen et al. (2008), MAPE values of less than 10% signify highly accurate forecasting, 10-20% is good forecasting, 20-50% is reasonable forecasting, and 50% or more is inaccurate forecasting.

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

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

Direction of Change (DC)

The DC criterion measures of the percentage of forecasts that accurately predict the correct direction of change (Hassani et al., 2013b). DC is an equally important measure, as the RMSE, for evaluating the forecasting performance of tourism demand models. This is because it is important that for example, when the actual series is illustrating an upwards trend, the forecast is able to predict that upward trend and vice versa. In brief, for the univariate case, for forecasts obtained using X_T, let D_{Xi} be equal to 1 if the forecast is able to correctly predict the actual direction of change and 0 otherwise. Then, $\tilde{D}_X = \sum_{i=1}^{n} D_{Xi}/n$ shows the proportion of forecasts that correctly identify the direction of change in the actual series.

5 Empirical Results

This section reports the out-of-sample forecasting results from both SSA and MSSA. Our analysis also considered the performance of optimized ARIMA and Exponential Smoothing models in relation to the proposed MSSA algorithms and the results which are not reported here showed the forecasts from MSSA outperforming these two models with statistically significant outcomes on most instances. It is noteworthy that the optimal ARIMA models were all seasonal ARIMA models and the related forecasts/results are available upon request. It is important to note that the aim here is not only the direct comparison of univariate SSA forecasts with the optimized MSSA algorithm, but also providing answers to a more interesting question. That is, can tourist arrivals from other countries in Europe act as leading indicators for another European country's tourist arrivals? Also, what is the extent to which this new optimized MSSA algorithm can improve upon the basic univariate forecasting results if applied for forecasting European tourist arrivals? The resulting output for each country is presented in Table 5.

Let us begin by considering the univariate SSA forecasts for European tourist arrivals. Firstly, we see that SSA-R is able to provide the best univariate forecast across all horizons for Greece, Cyprus and United Kingdom in comparison to SSA-V. Likewise, SSA-V forecasts are seen providing the best univariate forecast across all horizons for Netherlands. In terms of overall performance across all European countries considered here, based on the number of times one univariate forecast outperforms another we can conclude that SSA-R is the better univariate SSA model for forecasting tourist arrivals in these countries. The conclusions remain similar based on the model which reports the highest number of cases with the lowest average RMSE across all horizons. If forecasting a particular horizon using a univariate SSA model is of interest, then the informative results table enables practitioners to select the most appropriate SSA model based on the horizon of interest. However, it is noteworthy that basic SSA is unable to outperform the automated HMSSA algorithm on any of the cases in this study which is reflected by the 0% score. This goes on to prove the superiority of the proposed automated

MSSA algorithm over basic SSA and provides justification for presenting it as an improved, viable alternative for modelling and forecasting tourist arrivals.

Next let us consider the MSSA forecasting results. These results have been generated by evaluating every possible combination of tourist arrivals to determine which combination is able to report the lowest RMSE in comparison to the univariate SSA forecasts. In fact, the MSSA forecast for each country, using the data on arrivals from different selected countries, produced better forecasts than the univariate SSA in most cases. However, to save space, for each country only the case which gave the best out of sample forecasts (in terms of RMSE) are reported in Table 5. The first observation is that the only instance whereby a MSSA model is able to report the best forecast across all horizons is the HMSSA-V model for Portugal. The percentage score criterion indicates that HMSSA-R captures the overall best forecast in 36% of the cases in this study whilst HMSSA-V succeeds in providing the overall best forecast in 64% of the cases. Therefore, should one be interested in a single model for forecasting European tourist arrivals, we are able to present HMSSA-V as the feasible option which most certainly outperforms SSA forecasts, and also HMSSA-R forecasts in majority of the cases. Once again, as with the univariate forecasts, practitioners have the option of selecting the best MSSA model for a given country depending on the forecasting horizon of interest should one wish to consider a combined forecasting approach which in turn will enable minimising the forecast error.

The conclusions drawn above are based solely on the RMSE criterion without any tests for statistical significance. In order to provide a more statistically reliable grounding to these conclusions we consider the Hassani-Silva (HS) test for predictive accuracy in Hassani and Silva (2015). The one-sided HS test is able to show whether the model reporting the lowest RMSE also reports a lower stochastic error in comparison to another model. The resulting output is indicated in Table 5 and we are 90% confident in the outcomes which are found to be statistically significant in this case.

Table 5 also reports the RRMSE criterion which enables quantifying the comparative performance between two forecasting models based on the RMSE. For example, consider the average RRMSE values for Austrian tourist arrivals. The $\frac{HMSSA-R}{SSA-R}$ value of 0.68 indicates that HMSSA-R forecasts are on average 32% better than SSA-R forecasts. Likewise, the average $\frac{HMSSA-V}{SSA-V}$ value of 0.71 indicates that HMSSA-V forecasts are on average 29% better than SSA-V forecasts. The calculation of RRMSE's are further exploited to promote good statistical practice. More specifically, we test all the out-of-sample forecasts for statistical significance using not only the modified Diebold-Mariano (DM) test (Harvey et al., 1997), but also the two-sided HS test (Hassani and Silva, 2015). This enables to provide further justification for the leading indicators which are reported in what follows. Based on the DM test, it appears that even though there are considerable gains via MSSA over SSA in the case of Italy and Netherlands tourist arrivals forecasts, these are more likely to be chance occurrences because of the low number of statistically significant outcomes. However, in terms of the other eight countries there exists a considerably high number of statistically significant outcomes which provides sufficient evidence for the superiority of the MSSA forecasts over SSA. As a percentage, HMSSA-R forecasts are significantly better than SSA-R forecasts in 52% of the cases whilst HMSSA-V forecasts are significantly better than SSA-V forecasts in 74% of the cases. Accordingly, there is strong evidence to justify that the automated HMSSA-V forecast is indeed more powerful in terms of providing accurate forecasts in comparison to basic SSA-V forecasts.

In general, the RMSE, RRMSE and tests for statistical significance suggests that the MSSA models are able to provide significantly better forecasts than SSA in most instances for the European tourist arrivals series considered in this study. Next, we wish to ascertain whether there is sufficient evidence to promote the MSSA models used in this study as best in general for forecasting European tourist arrivals at particular horizons. For this purpose we begin by generating the empirical cumulative distribution functions (c.d.f.'s) for the absolute value of all forecast errors from all models at each horizon. According to Hassani et al. (2009;2013b), if the c.d.f. of absolute value of forecast errors lies above and hence to left of another c.d.f. of absolute value of forecast errors, then the model which lies towards the left and above has a smaller stochastic error. Figure 3 below presents the empirical c.d.f. for the absolute value of forecast errors across all countries and all horizons. However, it is clear that drawing conclusions based on Figure 3 alone can be problematic as the result is not very clear except for at $h = 24$ steps ahead. Therefore, we call on the one-sided HS test (Hassani and Silva, 2015). Based on the one-sided HS test (results available upon request) we can conclude with 95% confidence that in general, for forecasting European tourist arrivals across all horizons in the countries considered here, on average the MSSA models will report lower stochastic errors than the SSA models.

Thereafter, all forecasting results are tested for their ability at predicting the correct direction of change. The results are reported in Table 6 and all observations are once again tested for statistical significance via a Student's t test as done in Hassani et al. (2009;2013b). In brief, the DC criterion checks the forecasts against the actual values to determine whether the predictions are accurately picking up the actual direction of change as per the actual data values. The DC results indicate that on average, SSA-V provides the better DC prediction in relation to its univariate counterpart whilst HMSSA-V outperforms HMSSA-R based on the number of times one model provides a comparatively better average than the other model. Overall, there is clear evidence which points towards the capability of the automated MSSA algorithms at providing more accurate DC predictions than SSA with the only exception being tourist arrivals in Sweden for which SSA-V outperforms the MSSA models in providing the best average DC prediction.

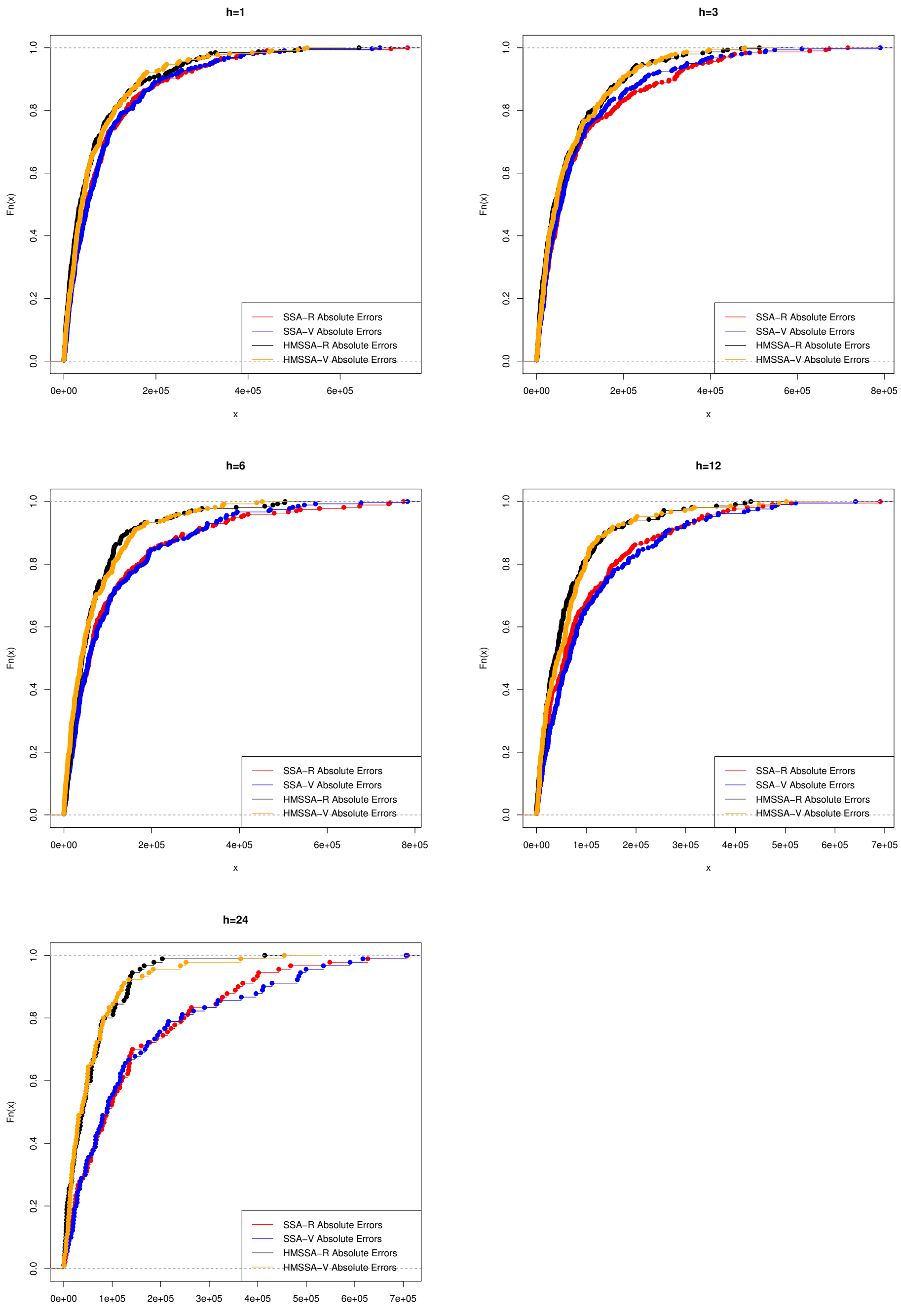

Figure 3: The cumulative distribution functions for the squared out-of-sample forecast errors.

Table 5: MSSA out-of-sample forecasting results for European tourist arrivals.

Country	h	SSA-R	SSA-V	HMSSA-R	HMSSA-V	$\frac{HMSSA-R}{SSA-R}$	$\frac{HMSSA-V}{SSA-V}$
Austria	1	111899	110669†	92800	**89603**	0.83	0.81*
(Greece)	3	104308	97258†	77932	**74688**	0.75*	0.77*
	6	99183†	100631	87844	**82518**	0.89	0.82
	12	96732	92983†	80730	**73015**	0.83	0.79*
	24	167380	131438†	**55801**$^{\checkmark}$	58770	0.33*	0.45*
Avg.		115900	106596†	79021	**75719**	0.68	0.71
Greece	1	87807†	90421	65564	**58577**$^{\checkmark}$	0.75$^{\flat}$	0.65$^{\flat}$*
(Germany)	3	151700†	161642	97105	**92405**$^{\checkmark}$	0.64*	0.57$^{\flat}$*
	6	157592†	174413	81939	**76288**$^{\checkmark}$	0.52	0.44$^{\flat}$*
	12	173704†	198750	**68750**$^{\checkmark}$	75966	0.40	0.38$^{\flat}$*
	24	177537†	156307	**33166**$^{\checkmark}$	48783	0.19$^{\flat}$*	0.31$^{\flat}$*
Avg.		149668†	156307	**69305**	70404	0.46	0.45
Germany	1	66278†	66754	52557	**52508**	0.79*	0.79*
(Sweden)	3	69996†	74657	55486	**50532**	0.79	0.68*
	6	74054†	84512	54285	**49420**$^{\checkmark}$	0.73$^{\flat}$	0.58$^{\flat}$*
	12	53384†	71809	**40557**	44671	0.76*	0.62$^{\flat}$*
	24	82974	79860†	**46497**	47384	0.56*	0.59*
Avg.		69337†	75518	49876	**48903**	0.72	0.65
Sweden	1	27880†	30150	**23212**	23436	0.83	0.78*
(Cyprus)	3	24230	23912†	20526	**19680**	0.85*	0.82*
	6	25766	24282†	18883	**18419**	0.73*	0.76
	12	26986	26318†	**18562**	18563	0.69*	0.71*
	24	34386†	49615	19257	**19098**	0.56*	0.38*
Avg.		27850†	30855	20088	**19839**	0.72	0.64
Cyprus	1	14132†	12452	8658	**7980**	0.61*	0.64*
(Germany)	3	17722†	19309	**9955**$^{\checkmark}$	10902	0.56$^{\flat}$*	0.56$^{\flat}$*
	6	17923†	25103	12520	**11962**$^{\checkmark}$	0.70$^{\flat}$	0.48$^{\flat}$*
	12	21241†	27319	10556	**9335**$^{\checkmark}$	0.50$^{\flat}$	0.34$^{\flat}$
	24	33875†	36938	**7326**$^{\checkmark}$	7523	0.22$^{\flat}$*	0.20$^{\flat}$*
Avg.		20979†	24224	9803	**9540**	0.47	0.39
Spain	1	197206	187053†	**142461**$^{\checkmark}$	148727	0.72$^{\flat}$*	0.80$^{\flat}$*
(Sweden)	3	343912	258974†	175976	**173150**	0.51$^{\flat}$*	0.67*
	6	396543	319133†	**114319**$^{\checkmark}$	128333	0.29$^{\flat}$*	0.40$^{\flat}$*
	12	227745†	273338	**108464**$^{\checkmark}$	112688	0.48$^{\flat}$*	0.41$^{\flat}$*
	24	409057†	474835	**114004**$^{\checkmark}$	122073	0.28$^{\flat}$	0.26$^{\flat}$
Avg.		314893	302667†	**131045**	136994	0.42	0.45
Italy	1	273286	269987†	248531	**229179**	0.91	0.85
(Austria)	3	243894†	247843	207941	**199873**	0.85	0.81
	6	248764	247302†	202005	**170874**	0.81	0.69
	12	256370	230185†	**175028**$^{\checkmark}$	187706	0.68	0.82
	24	298978	289067†	**179682**	216674	0.60*	0.75*
Avg.		264258	256877†	202637	**200861**	0.77	0.78
Netherlands	1	80036	79624†	65068	**63933**	0.81	0.80
(Greece)	3	75227	72825†	**56878**	56920	0.76	0.78
	6	78755	76307†	64679	**60555**	0.82	0.79
	12	86821	82871†	65424	**59411**	0.75*	0.72*
	24	126767	114085†	**65408**	68542	0.52*	0.60*
Avg.		89521	85142†	63491	**61872**	0.71	0.73
Portugal	1	45565	43899†	28473	**28085**	0.62*	0.64*
(Germany)	3	52128†	53920	30806	**28624**$^{\checkmark}$	0.59$^{\flat}$*	0.53$^{\flat}$*
	6	58928†	65085	31997	**28671**$^{\checkmark}$	0.54$^{\flat}$	0.44$^{\flat}$*
	12	68175†	75607	32644	**32281**$^{\checkmark}$	0.48$^{\flat}$	0.43$^{\flat}$
	24	97214†	102602	21620	**21395**$^{\checkmark}$	0.22$^{\flat}$*	0.21$^{\flat}$*
Avg.		64402†	68223	29108	**27811**	0.45	0.41
United Kingdom	1	214170†	219075	177166	**173528**	0.83	0.79*
(Germany)	3	225354†	238796	205742	**203511**	0.91	0.85
	6	232604†	244749	177167	**173529**	0.76	0.71
	12	222035†	226785	**192323**	204406	0.87*	0.90*
	24	280366†	322121	89014	**58316**$^{\checkmark}$	0.32$^{\flat}$*	0.18$^{\flat}$*
Avg.		234906†	250305	168282	**162658**	0.72	0.65
% Score		0%	0%	36%	64%		

Note: The leading indicator which is shown in brackets is only relevant for MSSA. Only the country which gave the best results is reported in bracket for MSSA. † indicates the best performing univariate model. Bold font indicates overall best performing model. % Score reflects the number of cases whereby a model reports the best overall forecast. $^{\checkmark}$ indicates the best performing model has a stochastically smaller error in comparison to its univariate counterpart based on the one-sided HS test at $p = 0.10$. $^{\flat}$ indicates a statistically significant difference between the distribution of forecasts based on the two-sided HS test at $p = 0.10$. * indicates a statistically significant difference between the MSSA forecast and the best univariate forecast based on the modified Diebold-Mariano test at $p = 0.10$.

Table 6: Direction of change results for European tourist arrivals.

h	Germany	Greece	Spain	Italy	Cyprus	Netherlands	Austria	Portugal	Sweden	UK
SSA-R										
1	0.97*	0.88*	0.88*	0.97*	0.84*	0.81*	0.91*	0.94*	0.94*	0.84*
3	0.60	0.50	0.57	0.47	0.33	0.57	0.60	0.60	0.47	0.63
6	0.67	0.52	0.48	0.44	0.30	0.48	0.48	0.74*	0.41	0.56
12	0.57	0.52	0.86*	0.57	0.33	0.43	0.48	0.81*	0.48	0.67
24	0.78	0.33	1.00*	0.89*	0.22	0.78	0.78	1.00*	0.44	0.89*
Avg.	0.72	0.55	0.76	0.67	0.41	0.61	0.65	0.82	0.55	0.72
SSA-V										
1	0.97*	0.88*	0.97*	0.94*	0.88*	0.84*	0.91*	0.94*	0.94*	0.84*
3	0.93*	0.93*	1.00*	1.00*	1.00*	0.93*	0.93*	0.97*	0.97*	0.97*
6	1.00*	1.00*	1.00*	1.00*	1.00*	1.00*	0.89*	1.00*	0.85*	0.93*
12	0.90*	0.43	0.48	0.67	0.38	0.81*	0.81*	0.57	0.76*	0.76*
24	1.00*	0.67	0.11	0.78	0.67	0.78	0.78	0.78	0.78	0.56
Avg.	0.96	0.78	0.71	0.88	0.78	0.87	0.86	0.85	**0.86**	0.81
HMSSA-R										
1	1.00*	0.88*	1.00*	0.91*	0.94*	0.88*	0.91*	1.00*	0.94*	0.88*
3	1.00*	1.00*	1.00*	0.97*	1.00*	0.93*	1.00*	1.00*	1.00*	0.93*
6	1.00*	1.00*	1.00*	0.93*	1.00*	1.00*	0.89*	0.93*	0.89*	0.89*
12	1.00*	0.71	0.81*	0.81*	0.67	0.71	0.86*	0.90*	0.43	0.86*
24	1.00*	1.00*	0.89*	1.00*	1.00*	0.78*	1.00*	1.00*	0.67	1.00*
Avg.	**1.00**	0.92	**0.94**	0.92	0.92	**0.86**	**0.93**	0.97	0.78	**0.91**
HMSSA-V										
1	0.97*	0.91*	1.00*	0.94*	1.00*	0.81*	0.94*	1.00*	0.84*	0.84*
3	1.00*	0.97*	1.00*	1.00*	0.97*	0.90*	0.97*	1.00*	0.97*	0.93*
6	1.00*	1.00*	1.00*	0.96*	1.00*	1.00*	0.89*	0.96*	0.96*	0.93*
12	1.00*	0.81*	0.76*	0.90*	0.81*	0.71	0.71	0.95*	0.67	0.86*
24	1.00*	1.00*	0.89*	1.00*	1.00*	0.78*	1.00*	1.00*	0.67	1.00*
Avg.	0.99	**0.94**	0.93	**0.96**	**0.96**	0.84	0.90	**0.98**	0.82	**0.91**

Note: Shown in bold font is the model reporting the best average DC prediction across all horizons for a given country. * indicates the DC predictions are statistically significant based on a t-test at $p = 0.05$.

6 Discussion

6.1 Merits and Demerits of SSA/MSSA

We begin by discussing the merits these two techniques further. Firstly, parametric assumptions are unlikely to hold in the real world and therefore the use of parametric techniques usually result in the need for data transformations which leads to a loss of information as noted in Hassani et al. (2013a). However, because SSA and MSSA do not make any assumptions about the signal or the noise component of the data, and do not depend on any parametric model for the trend or oscillations, there is no requirement for data transformations nor any loss of information when using these approaches (Hassani et al. (2013a). Secondly, the noise reduction feature in SSA/MSSA is not present in classical time series analysis and forecasting methods. Filtering enables SSA/MSSA to provide a better fit to the data and obtain more accurate forecasts. Thirdly, SSA/MSSA techniques can extract signals in time series. This enables to obtain a richer understanding of the dynamics underlying time series by analysing the trend and seasonal fluctuations in isolation. Fourthly, SSA/MSSA can forecast a particular signal which is of interest, such as extracting and forecasting the trend alone, or 12 or 3-month seasonal fluctuations depending on the requirements. However, these techniques are not without its limitations. Based on the authors' experience, SSA/MSSA are most useful when faced with seasonal data. Secondly, parametric models are preferred for certain scenarios as unlike with SSA/MSSA, the 'parameters' (e.g. regression parameters) enable interpretations on the exact effect of a given independent variable on a dependent variable. Moreover, there are a variety of historical literature based on parametric models which allows users to easily compare and contrast between the findings. In addition, SSA/MSSA are highly sensitive to the selection of L and r which can be done by following a binary approach (Hassani et al., 2015) or the recently introduced Colonial Theory (CT) based approach (Hassani et al., 2016). Whilst some may argue that the decomposition process could lead to a loss of some deterministic structures, the CT based approach in Hassani et al. (2016) helps overcome this issue to a certain extent. Moreover, there is always the possibility of applying sequential SSA (see, Sanei and Hassani, 2015) to extract any deterministic structures mixed up in the residual.

6.2 Exogenous Events and its Impact on SSA/MSSA based Modelling

The tourism industry is deeply affected by exogenous and uncontrollable events such as terrorist attacks, natural disasters, recessions and political instability (among others). Whilst an in-depth discussion of the impact of such events on the primary modelling techniques are beyond the mandate of this paper, we briefly comment on the potential impact of such events within the proposed models. Those interested are referred to Chen (2005) where the author provides a concise account of the impact of intervention events on tourist flows when forecasting with both parametric and nonparametric forecasting techniques. In relation to parametric techniques, the nonparametric nature of SSA/MSSA is likely to ensure these models are less sensitive to external shocks. For example, according to Hassani et al. (2013c) which was a collaboration with the Office for National Statistics in UK, following an application of SSA, ARIMA and Holt-Winters (HW) to eight UK economic time series before, during and after the recession, the authors found that SSA is least sensitive to the impact of the recession in relation to ARIMA and HW as it produced comparatively superior forecasting results. More recently, Silva and Hassani (2015) evaluated the impact of the 2008 recession on forecasting US trade with SSA in relation to the optimal ARIMA and ETS models, and Neural Networks. Here, the authors found compelling evidence to conclude that SSA is indeed comparatively less sensitive to the the impacts of recessions on the modelling process. There is yet a published evaluation of the impact of such exogenous events on the MSSA modelling procedure, but given that MSSA is essentially the extension of SSA for multiple time series, it is reasonable to expect similar (or even better) outcomes.

6.3 Explanations for the resulting Leading Indicators

The MSSA algorithm for leading indicators has been successful at identifying leading cross country relations for tourism demand in Europe with statistically significant evidence. Here, we seek to provide possible theoretical explanations for this behaviour. In the process, we look at the concept of causality. This concept is useful, as in MSSA it is not correlation between series that determines how well two series can work together, but instead as Sanei and Hassani (2015) note, it is the similarity and orthogonality among series which play an important role. Unlike correlation, causality seeks to determine whether one series causes another. As such, we perform a test for Granger causality on all leading indicator pairs to determine whether there is sufficient evidence to conclude that leading indicators identified via the MSSA modelling process actually causes the main series. The test results are reported via Table 7. Looking at the results clearly indicate that those series we have selected as leading indicators via MSSA do in fact cause the main series. Accordingly, we can conclude that causality is one theoretical explanation for the leading indicators identified within this study.

Table 7: Additional information for leading indicators identified through this study.

Main Series (Leading Indicator)	Causality	Granger (p-value)
Austria (Greece)	Greece $\rightrightarrows$ Austria	0.03*
Greece (Germany)	Germany $\rightrightarrows$ Greece	<0.01*
Germany (Sweden)	Sweden $\rightrightarrows$ Germany	<0.01*
Sweden (Cyprus)	Cyprus $\rightrightarrows$ Sweden	<0.01*
Cyprus (Germany)	Germany $\rightrightarrows$ Cyprus	<0.01*
Spain (Sweden)	Sweden $\rightrightarrows$ Spain	<0.01*
Italy (Austria)	Austria $\rightrightarrows$ Italy	<0.01*
Netherlands (Greece)	Greece $\rightrightarrows$ Netherlands	<0.01*
Portugal (Germany)	Germany $\rightrightarrows$ Portugal	<0.01*
UK (Germany)	Germany $\rightrightarrows$ UK	<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 0.05.

7 Conclusion

This study not only marks the introductory application of Multivariate SSA for tourism demand forecasting, but also the first instance whereby the automated MSSA algorithm is used in cross country data for European tourist arrivals. We used the data on tourist arrivals from ten European nations and obtained the forecast over the short, medium and long term horizons using vector and recurrent forecasting algorithms of SSA and MSSA. The data was initially tested for normality, seasonal unit root and structural breaks prior to the forecasting exercise. The out-of-sample forecasting results were evaluated and distinguished using two important metrics, i.e. the RMSE for measuring the accuracy of the forecasts and the direction of change criterion to determine the ability of each model to predict the percentage of correct direction of change.

Our results indicate that for univariate forecasting, should a single model be of interest, then SSA-R is on average better than SSA-V across all countries and all horizons considered in this study. Likewise, for multivariate forecasting, we found that, on average, HMSSA-V is better than HMSSA-R. It is noteworthy that the multivariate forecasting exercise has considered all possible combinations of cross country relations to tourist arrivals, and to save space we only report the combinations which minimize the out-of-sample forecasting error. The forecasting results were tested for statistical significance, not only via the modified DM test in Harvey et al. (1997), but also via the recently introduced Hassani-Silva (HS) test in Hassani and Silva (2015). We obtained a high number of statistically significant outcomes in this study, providing convincing evidence for the results. Overall, it is concluded that the automated MSSA algorithms outperformed univariate SSA based on both the RMSE and DC criteria.

The presentation of the results itself are extremely useful to practitioners as it enables them to obtain the best SSA/MSSA models for forecasting the European tourist arrivals based on the horizon of interest and forecasting objectives. The study can benefit both forecasters and policy makers in a variety of ways. For forecasters, it is a guide to obtain the best out-of-sample forecasts in a multivariate framework. For policy makers, these results help them to make the right policies, in planning, resource allocations and investment decisions.

As the aim of this study was mainly to use the common pattern in European tourist arrivals to see if better forecasts can obtained, it has not considered other range of tourist and travel indicators in the present analysis. Accordingly, the algorithm we propose is optimized to obtain the best possible forecast with MSSA as opposed to an optimal signal extraction. Future studies should consider applying the proposed automated MSSA algorithm using various socioeconomic indicators for forecasting European tourist arrivals as well as investigating the impact of exogenous shock on MSSA modelling. It is also acknowledged that this study has only investigated the tourist arrivals for selected European countries which are established or growing destinations and it does not intend to represent Europe as a continent. Also, the present study only considered the bi-variate Singular Spectrum Analysis. There is scope to develop the method as a general multivariate SSA in which one could jointly consider all ten series together and simultaneously produce the forecasts for all countries.

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Appendix

Table 8: Out-of-sample forecasting MAE and MAPE (%) based results for European tourist arrivals.

Country	h	SSA-R	SSA-V	HMSSA-R	HMSSA-V	SSA-R	SSA-V	HMSSA-R	HMSSA-V
Austria	1	89239	90428	**68812**	72542	5.82%	5.46%	**4.34%**	4.46%
(Greece)	3	82547	81845	63225	**62191**	5.42%	4.89%	4.08%	**3.86%**
	6	80413	82468	73971	**67795**	5.57%	5.18%	4.82%	**4.22%**
	12	82072	75084	66686	**60368**	5.33%	4.53%	3.92%	**3.74%**
	24	138749	120110	**40719**	54400	9.91%	7.42%	**2.88%**	3.68%
Greece	1	69363	74593	53077	**46653**	15.55%	16.10%	**12.80%**	15.79%
(Germany)	3	116370	133169	78995	**74691**	26.09%	35.95%	**24.79%**	25.56%
	6	120022	138280	67206	**62774**	28.13%	46.51%	**18.84%**	25.06%
	12	127749	157419	**53509**	63435	13.99%	17.40%	**13.63%**	16.98%
	24	140540	136615	**27765**	44200	12.79%	14.47%	**5.35%**	9.66%
Germany	1	54875	55666	**41726**	44774	2.26%	2.30%	**1.71%**	1.80%
(Sweden)	3	57565	59491	44352	**41640**	2.37%	2.47%	1.84%	**1.76%**
	6	59001	68290	41562	**36593**	2.58%	2.92%	1.82%	**1.53%**
	12	43248	63899	**32812**	33846	1.71%	2.49%	**1.28%**	1.32%
	24	74311	55951	38643	**38014**	2.63%	1.99%	1.36%	**1.33%**
Sweden	1	18988	22363	**27126**	43252	6.62%	9.89%	**4.42%**	6.15%
(Cyprus)	3	17311	17878	**27496**	33782	7.85%	8.27%	**4.39%**	5.27%
	6	18547	18295	**29098**	33427	9.28%	11.29%	**4.78%**	5.92%
	12	19817	20602	**24799**	31809	7.16%	7.63%	**4.66%**	5.76%
	24	26580	39909	**58411**	74179	11.94%	15.40%	**6.11%**	10.31%
Cyprus	1	10716	9699	**6711**	6857	12.55%	9.95%	8.14%	**7.38%**
(Germany)	3	14633	15573	**7692**	9335	18.71%	19.29%	**8.85%**	10.21%
	6	15217	20818	10086	**8401**	21.32%	30.99%	11.56%	**8.25%**
	12	17069	21552	8044	**7538**	23.43%	33.68%	**7.19%**	8.54%
	24	26995	27847	**5704**	6621	52.36%	53.51%	**32.79%**	38.10%
Spain	1	164018	153992	**105929**	118294	4.72%	3.95%	**2.80%**	3.24%
(Sweden)	3	291764	190586	**128557**	139918	9.25%	3.94%	**3.73%**	3.75%
	6	320137	256566	**93275**	108159	9.42%	3.88%	**2.73%**	3.14%
	12	182026	241634	**85511**	93568	4.74%	3.42%	**2.11%**	2.41%
	24	366340	432951	98029	**93385**	8.90%	3.91%	2.52%	**2.11%**
Italy	1	208810	209271	202284	**183592**	6.33%	6.35%	5.98%	**5.12%**
(Austria)	3	190883	188841	174311	**170792**	6.43%	6.39%	**5.30%**	5.75%
	6	195057	189930	142970	**131047**	6.95%	6.46%	**3.52%**	4.33%
	12	205026	177183	**133333**	146462	5.95%	5.18%	**3.29%**	3.85%
	24	248823	226335	**144262**	158009	5.47%	4.71%	**3.18%**	4.25%
Netherlands	1	57657	58568	**48965**	49836	5.57%	5.65%	**4.77%**	4.92%
(Greece)	3	55126	53197	44485	**40069**	5.42%	5.18%	**4.50%**	4.06%
	6	58294	55771	**47703**	48071	5.72%	5.45%	**4.70%**	4.74%
	12	64869	64314	51260	**46265**	5.91%	5.99%	4.86%	**4.54%**
	24	86219	84587	56842	**54533**	6.96%	7.08%	4.66%	**4.46%**
Portugal	1	36071	35196	**23129**	23246	6.34%	6.33%	**4.10%**	3.89%
(Germany)	3	40317	42970	25750	**24910**	7.14%	7.73%	**4.42%**	4.32%
	6	46687	54123	27967	**24407**	8.21%	9.85%	5.37%	**4.44%**
	12	55034	58835	**25154**	26197	8.36%	9.09%	3.76%	**3.61%**
	24	88371	98378	**18976**	20150	11.64%	13.30%	**2.29%**	2.67%
United Kingdom	1	164771	171971	127609	**118009**	8.57%	8.83%	**6.43%**	5.97%
(Germany)	3	176758	186043	175888	**172726**	10.54%	10.47%	**9.02%**	9.58%
	6	182763	192892	**155462**	167744	9.47%	9.96%	**8.16%**	9.22%
	12	176798	178960	**146940**	150595	8.11%	8.12%	7.11%	**6.99%**
	24	237081	274782	73457	**47874**	9.53%	10.99%	3.41%	**2.35%**

Note: The leading indicator which is shown in brackets is only relevant for MSSA. Bold font indicates overall best performing model under each criteria.